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Assessing Residential Socioeconomic Factors Associated With Pollutant Releases Using EPA's Toxic Release Inventory

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ASSESSING RESIDENTIAL SOCIOECONOMIC FACTORS ASSOCIATED WITH POLLUTANT RELEASES USING EPA'S TOXIC RELEASE INVENTORY

By

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ABSTRACT

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It has been demonstrated that certain demographic groups – particularly minorities and low-income individuals – live disproportionately closer to polluting facilities. Therefore, we investigated the chemical releases from Toxic Release Inventory (TRI) facilities in four counties in Upstate New York (Albany, Erie, Monroe, and Onondaga Counties). Using hierarchal clustering, we created seven unique residential clusters from nine population demographics. We geocoded the polluting facilities into our residential clusters to determine if any demographic group was disproportionately exposed to the presence of TRI facilities. Next, the quantity, in pounds, of chemicals released were calculated, the chemicals released were weighted based upon their potential toxicity, and the Facility Scores from EPA's Risk-Screening Environmental Indicators (RSEI) Model were obtained; the top five facilities with the highest Facility Scores per cluster were examined in detail to determine if any population demographic were disproportionately exposed to more severe chemicals.

Key words: TRI Facilities, clustering, socioeconomic factors, RSEI Model, environmental justice, chemical pollutants

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CHAPTER 1: INTRODUCTION

The Environmental Justice Movement

The late 1950s saw the rise of the Civil Rights Movement – a struggle for social justice and equity for African American citizens in the United States to gain equal rights (Onion et al., 2019). While this unprecedented fight spanned nearly two decades, in 1964 the Civil Rights Act was established which guaranteed equal employment for all, limited use of voter literacy tests, and banned segregation of public facilities by federal authorities (Onion et al., 2019). As the movement continued, the question of public health dangers for African American communities and families began to rise. In 1968, African Americans mobilized to oppose what they considered environmental injustice for the first time; in this instance, they were fighting for better working conditions and pay for garbage workers striking in Memphis, Tennessee (United States Environmental Protection Agency, 2017c). The second mobilization of African Americans to oppose environmental injustice was a nonviolent sit-in protest in Warren County, North Carolina (United States Environmental Protection Agency, 2017c). Warren County was overwhelmingly comprised of poor residents and minorities, and the state government decided to place a polychlorinated biphenyl (PCB) landfill within this county (Skelton & Miller, 2016). Furious over their dismissed concerns, the residents of Warren County stopped trucks from getting to the landfill by lying in the streets. Eventually, 500 people were arrested over these protests. These arrests were the first in United States history made over the siting of a landfill (Skelton & Miller, 2016). While the people of Warren County did eventually lose their battle, other communities of color began to organize to protect their space and environment (Skelton & Miller, 2016). This small movement in North Carolina is widely credited as the birth of the Environmental Justice Movement (United States Environmental Protection Agency, 2017c).

With the Warren County sit-in fueling marginalized groups across the county, in 1983 the General Accounting Office (GAO) conducted a study on the racial and economic characteristics of communities surrounding four hazardous waste landfills in three southeastern states: North Carolina, South Carolina, and Alabama (General Accounting Office, 1983). They did this by looking at where the landfills were located and the demographics of the surrounding communities; to get the community level data, the GAO utilized 1980 U.S. Census data. What they found was that three out of the four hazardous waste facilities examined were in communities with populations comprised of at least 26% African Americans. Further, the families living in these communities were also earning incomes below the poverty level (General Accounting Office, 1983; United States Environmental Protection Agency, 2017c). The results of this study sparked the Environmental Justice Movement by providing empirical support for their claims of environmental racism (United States Environmental Protection Agency, 2017c). Shortly after the report from the GAO, another group, The United Church of Christ Commission on Racial Justice, completed similar work examining the relationship between the location of hazardous waste sites and the racial and socioeconomic compositions of communities hosting these hazardous waste sites nationwide (Commission for Racial Justice, 1987; United States Environmental Protection Agency, 2017c). The authors found that over 15 million African Americans, 8 million Hispanics, and half of all Asian/Pacific Islanders and Native Americans resided in communities with at least one abandoned or uncontrolled toxic waste site. The study also showed that, while the socioeconomic status of the residents did appear to play a role, race was still the most significant factor (Commission for Racial Justice, 1987; United States Environmental Protection Agency, 2017c). This was the first study of its kind aimed at investigating the associations between race, class, and environmental pollution.

Work in the environmental justice field progressed over the coming years as various environmental networks and actions were formed to address environmental inequities in specific places or amongst specific groups of people. In 1991, the First National People of Color Environmental Leadership Summit was held in Washington D.C.. From this Summit, the 17 Principles of Environmental Justice were adopted. These Principles served as a platform for a national and international movement of all people (United States Environmental Protection Agency, 2017c). In 1992, the Environmental Protection Agency (EPA) created the Office of Environmental Equity, which was later changed to the Office of Environmental Justice (OEJ). The OEJ was established based on a recommendation from the Environmental Equity Workgroup. Soon after that, in 1993, the National Environmental Justice Advisory was created to hold public meetings on environmental justice issues across the county (United States Environmental Protection Agency, 2017c). In 1994, Executive Order 12898 (EO 12898), Federal Actions to Address Environmental Justice in Minority Populations and Low-Income Populations, was passed by the Clinton Administration. This order directed federal agencies to develop strategies on how to identify and address the human health and environmental effects on minority and low-income populations (United States Environmental Protection Agency, 2017c). The act also established an Interagency Working Group on environmental justice which was chaired by the EPA Administrator and included the heads of 11 different agency departments and several White House offices (United States Environmental Protection Agency, 2018a). Environmental justice was slowly gaining traction in the federal government and was on the way to becoming a staple within every office.

Soon after the Clinton administration's Executive Order went into place, states began creating their own environmental justice standards and bills. However, in 2007 Robert Bullard and his collaborators published a report called *Toxic Wastes and Race at Twenty* (Bullard et al., 2007; United States Environmental Protection Agency, 2017c). This report was an update to the report published by the United Church of Christ in the 1980s. The researchers found that, for all the attention environmental justice was gaining, problems of environmental justice and racism had actually managed to get worse. Changes such as government cutbacks in the enforcement of these laws and weakening health protection brought about new problems for minority and low-income communities. These changes, along with the evidence from Bullard's report, signified to Bullard that there was clear evidence of racism in where toxic waste sites were located, and in how government agencies responded to toxic contamination emergencies in communities comprised of minorities (Bullard et al., 2007). Four years after Bullard's report was published, Plan EJ 2014 was released by the US EPA (United States Environmental Protection Agency, 2017c). Plan EJ 2014 was a roadmap made to assist the EPA in incorporating environmental justice into all agency programs, policies, and activities (United States Environmental Protection Agency, 2017b). Various outcomes came from this plan, including development of nationally consistent environmental justice screening and mapping tools (United States Environmental Protection Agency, 2017b). A similar plan, EJ 2020, was published in 2015 to map the EPA's next phase of planning on environmental justice at the EPA (United States Environmental Protection Agency, 2017c). Finally, another agenda, EJ 2020 Action Agenda, was released by the EPA in 2016 to address the EPA's advancement of environmental justice from 2016 to 2020 (United States Environmental Protection Agency, 2017c). This action plan addressed eight priority areas and four national environmental justice challenges with the goal of making a more visible difference in environmental and public health outcomes for all people (United States Environmental Protection Agency, 2016).

Thus, as noted in the prior paragraphs, the EPA put forth a great deal of effort to make environmental justice part of its core mission. However, the EPA also wanted to make this information known to the public. Therefore, in 2015, the EPA released EJSCREEN. EJSCREEN is an online tool, available to the public, that provided information about how the agency was combining environmental justice with its work on protecting the public from the adverse health effects of environmental pollutants (United States Environmental Protection Agency, 2017c). The tool provides the EPA with a nationally consistent dataset and approach for combining environmental and demographic indicators; the tool itself includes 11 environmental indicators, 6 demographic indicators, and 11 environmental justice indices. The tool is user-friendly, by creating color coded maps to show area differences. It also gives the user the ability to create reports for a selected area, and can even compare selected areas to the state, EPA region, or nation (United States Environmental Protection Agency, 2019b).

The area of environmental justice is one that is always growing; new studies are continuously being published to address the inequities seen across the county. The field has grown to include not only race and income, but numerous other demographic and socioeconomic factors, such as gender, education, employment, and housing types. It is important to study this field because we are not addressing the inequities we have created today, but the inequities that were created years ago that still have a long-lasting effect. Institutional racism has shaped many areas across the states, but by studying and addressing them through an academic platform, we are able to inform not only the public but also the policy makers of these gross injustices. Pointing out these injustices can educate and shape the future generations, it can help institutions pinpoint where resources would be best utilized, and it can help make every community stronger. The Environmental Justice Movement was not started by powerful businessmen and women, but by community members who cared enough to stand up for what they believed in. Further commitment to the field not only can educate people, but it could bring about the next group of committed community members.

The online era

The EJSCREEN tool is not the only online tool that has been published by the EPA. Two other resources put out by the EPA include the Toxic Release Inventory (TRI) and the Risk-Screening Environmental Indicators (RSEI) model. Briefly, the TRI program tracks the management of more than 650 chemicals that have been classified as potentially posing a threat to human health and the environment. This information is then made publicly available so the average person can see what exactly is being stored, utilized, or released into their community (United States Environmental Protection Agency, 2019a). The RSEI model works directly with the TRI program, and assesses the potential impact of industrial chemical releases on the public (United States Environmental Protection Agency, 2019c). A diagram of the RSEI model can been seen in Figure 1 (United States Environmental Protection Agency, 2018b).

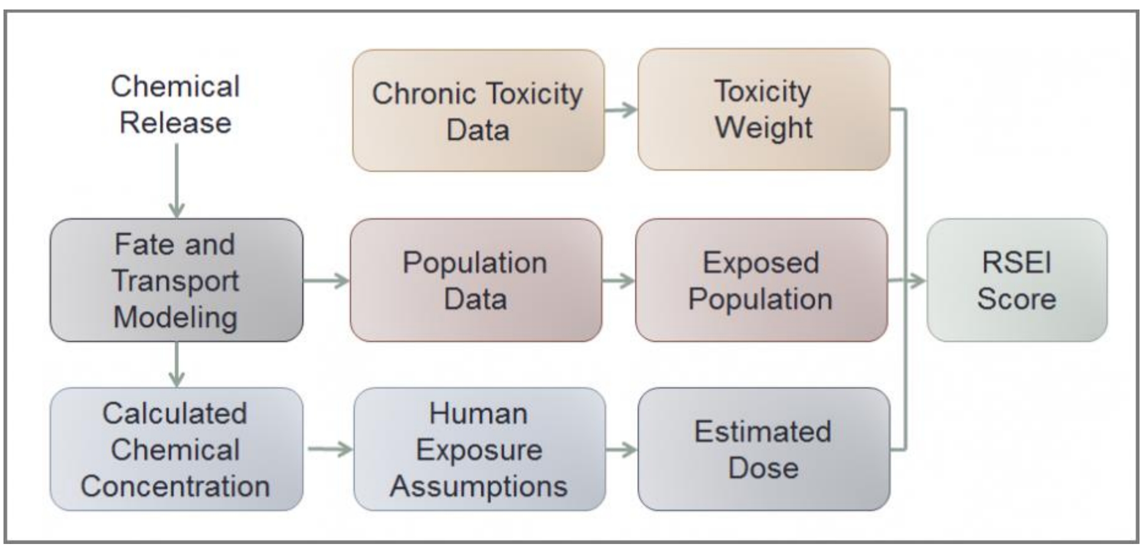

Figure 1. An infographic detailing the components of the RSEI Model

Source: (United States Environmental Protection Agency, 2018b)

As demonstrated in Figure 1, the RSEI model works by incorporating data on the quantity of chemicals, the relative toxicity of the chemicals, the chemical's fate and transport in the environment, and the potential human health exposure to establish comparable values known as RSEI Hazard Scores or RSEI Scores (United States Environmental Protection Agency, 2017a). RSEI Hazard Scores can be found by multiplying the pounds of chemicals released by the chemical's toxicity. RSEI Scores can be found by multiplying the estimated dose, the toxicity weight, and the number of potentially exposed people. These models can be used to help identify areas that may be more at risk to exposure of toxic chemicals. From this data, demographic information can be collected using other online databases, such as the U.S. Census. Combining TRI, RSEI, and demographic data together can help inform us if certain demographic groups are potentially more at risk for exposures to hazardous pollutants.

Our project design

Environmental justice studies can often yield differing levels of disproportionate exposure depending on the area the study is conducted in, and thus conclusions made about certain demographic groups should be viewed cautiously. While common conclusions are arrived at by multiple researchers, that should only be used as a guide so as not to make generalizations and induce bias. In their work, Sicotte (2010) states that even identical methodologies may yield varying patterns of inequity when applied to different metropolitan areas across the United States. For example, in South Carolina, the racial composition of block groups didn't predict the presence of polluting facilities or hazardous waste sites, but lower median incomes did (Cutter et al., 1996). However, in Phoenix, AZ, a positive association was seen between the number of hazardous waste sites and the population percentage of African

Americans and Latinos, but a negative association was seen with household income (Bolin et al., 2002).

In our work, we utilized what Mohai & Saha (2006) call the “unit-hazard coincidence” method. The approach identifies a predefined geographic unit, such as census tracts or block groups, identifies which units contain the hazard being studied, such as TRI facilities, then compares the demographic characteristics between which units containing the hazard and the units not containing the hazard. A limitation to this method is that it operates on the implicit assumption that those living in host units are closer to the hazards than those not living in the host units. This becomes as issue when the hazard is located near the edge of a host unit that may be bordering a non-host unit. Regardless, this method has been utilized by multiple national-level studies (Anderson et al., 1994; Anderton et al., 1997; Been, 1995; Commission for Racial Justice, 1987; Davidson & Anderton, 2000; Hamilton, 1995; Perlin et al., 1995; Ringquist, 1997; Zimmerman, 1993).

For our studies, we examined four counties in Upstate New York using U.S. Census block groups as our residential proxy; therefore, the conclusions of our study are specific to Upstate New York at the block group level only. We have included nine population demographic variables in our study, and, using a novel clustering method, we clustered those variables based upon their similarities. We then analyzed how the location of TRI facilities (Chapter 2) and the suspected toxicity of the releases from these facilities (Chapter 3) were associated with our selected demographic variables. The objective of our first study was to determine if our study area displayed any trends of having higher quantities of polluting facilities and chemical releases located in neighborhoods comprised of certain demographics. Our hypothesis for this study was that minorities and low-income households were going to be the two groups disproportionately exposed to both TRI facilities and higher quantities of pollutant releases. The objective of our second study was to determine if any demographic groups were exposed to higher concentrations of the most toxic chemicals. This was done by utilizing the RSEI model and weighting chemical releases. The hypothesis for this study was that those working in non-managerial positions were going to be the demographic that might be disproportionately exposed to more severe chemicals. Future work could be done on this study to include health data for these areas to determine if any areas of higher concern potentially developed health conditions as a result of industrial pollution.

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CHAPTER 2: ASSESSING RESIDENTIAL SOCIOECONOMIC FACTORS ASSOCIATED WITH POLLUTANT RELEASES USING EPA'S TOXIC RELEASE INVENTORY

Abstract

Environmental justice (EJ) scholars have shown that minorities and those who live in poverty are disproportionately exposed to the environmental hazards produced by industrial facilities. While these community characteristics are the most common focus of such EJ scholars, there are additional demographics that are relevant in the assessment of EJ patterns. The results of EJ studies tend to see different levels of disproportionate exposure amongst minorities in different locations, suggesting there is a geographic component at play. Thus, in this study we compare four counties in Upstate New York (Albany, Erie, Monroe, and Onondaga) located within 300 miles of one another. Nine census-based population identifiers assessing residential socioeconomic status (R-SES) were grouped together based upon similarities using hierarchal clustering. These identifiers, expressed as percentages, included the population with at least a high school degree, the population in owner occupied housing, the population below the poverty line, the population identifying as a race other than Non-Hispanic White, the population unemployed, the population in non-managerial positions, the number of single parent households, the amount of vacant housing in the area, and the amount of urban area. We estimated seven unique residential clusters across the four-county area and each cluster was spatially linked to proximate environmental hazards. While we did not see traditional EJ outcomes, we did find that workers who were employed in non-managerial positions were disproportionately exposed to industrial sources of pollution. Additionally, the R-SES cluster with one of the highest percentages of laborers in non-managerial positions (79% of residents) released over 5 million pounds of chemicals in 2000 alone. By comparison, the next highest

amount of chemicals released by any R-SES cluster was just under 3 million pounds, suggesting that people working in non-managerial positions are also disproportionately exposed to higher quantities of chemical pollutants. These findings suggest that, in addition to the assessment of race and class as predictors of community-level contamination, other metrics of socio-economic status and methodological strategies are helpful in understanding the complex landscape of environmental inequity.

Introduction

In 1984, the world's largest industrial disaster occurred in Bhopal, India. A gas leak of methylisocyanate occurred at the Union Carbide India Limited pesticide plant, resulting in the death or serious injury of over 2000 people (United States Environmental Protection Agency, 2019c). Two years later, in response to that event, the United States passed the Emergency Planning and Community Right-to-Know Act, also known as EPCRA. EPCRA requires federal, state, and local governments; tribes; and industries to have emergency plans in place in case an accident, such as a chemical release or leak, occurs. Section 313 of EPCRA established the Toxic Release Inventory (TRI) Program. This program tracks the management of over 650 toxic chemicals across the United States that may pose a threat to human and environmental health (United States Environmental Protection Agency, 2019d); the facilities that release chemicals are known as TRI facilities. Prior work has found that these facilities, other hazardous waste facilities, and dumps are disproportionately placed in areas with high concentrations of minorities and individuals below the poverty line (Bullard et al., 2007; Commission for Racial Justice, 1987; Mohai et al., 2009). The inequity of placing these facilities in high minority locations was one of numerous stimulants of the Environmental Justice Movement. The Movement began in the late 1980s and strives for fair treatment and meaningful involvement of all people, regardless of race, color, national origin, or income (United States Environmental Protection Agency, 2019a).

Studies using population demographics are often carried out by assessing both individual- and neighborhood-level socioeconomic status (SES). Individual-level SES includes variables that affect just the individual, whereas neighborhood-level SES includes variables that affect an entire group of people living in the same community. These SES variables are often ranked from high to low, with many studies stating that lower SES neighborhoods, typically comprised of minorities and low-income households, face the worst of environmental pollution from TRI and other hazardous waste facilities (Wilson et al., 2012). For instance, one of the most pivotal pieces in environmental justice literature was published in 1987 by the United Church of Christ Commission for Racial Justice. This study sought to test if minorities and low-income households were disproportionately exposed to commercial waste facilities. They found that race proved to be the most significant variable tested in association with the location of hazardous waste facilities (Commission for Racial Justice, 1987). In 2007, this report was updated to assess the progress of EJ within the United States. The report showed that issues of EJ in minority and low-income communities had gotten worse over the last twenty years, and that there were still clear signals of racism in where facilities were located (Bullard et al., 2007). However, there is another body of literature that states that other variables may also be influential in determining disproportionate exposure to environmental pollutants. For example, some researchers have found that people working as laborers are more likely to live near hazardous waste facilities (Boer et al., 1997; Williams, 2008). It is highly possible that the differing variables used in these studies (i.e. race, income), the number of variables tested, and the geographic scale (i.e. Census block groups, Census tracts) and geographic location of the work can all effect the outcomes of these studies.

In the past, researchers have identified several important demographic indicators that can be used to define a neighborhood. From those demographics an index could be created to define the socioeconomic status of a community (Messer et al., 2006). These factors could then be combined using principle component analysis (PCA). PCA is a mathematical reduction method used to reduce the dimensionality of larger data sets by taking a large set of variables and cutting them down to only include the variables representing the greatest variability (Mirowsky et al., 2017). After performing a PCA analysis, a deprivation score for each neighborhood being tested would be calculated. A deprivation score is a scale of how disadvantaged or deprived an area may be. However, recently work has begun using hierarchal clustering methods instead of PCA (Humphreys & Carr-Hill, 1991; Mirowsky et al., 2017; Weaver et al., 2019). Hierarchal clustering allows researchers to group residential neighborhoods together based upon similarities in their demographic characteristics and establish what are known as residential clusters. By creating residential clusters using hierarchical clustering, researchers can compare the levels of each selected variable in each cluster rather than grouping all indicators representing high levels of deprivation together.

The objective of this study was to determine whether we could find a trend in the distribution of TRI facilities in Upstate New York based upon population demographics. Additionally, we sought to assess whether there were larger quantities of chemical releases from these facilities present among certain population demographics. Our hypothesis for this study was that minorities and low-income households were going to be the two groups disproportionately exposed to both TRI facilities and higher quantities of pollutant releases. In our analysis, we utilized a hierarchal clustering method to understand how residential socioeconomic status (R-SES) is distributed across four counties located in Upstate, New York. With this method, we aggregated US Census block groups into seven residential clusters across Erie, Monroe, Onondaga, and Albany Counties. TRI facilities were then geocoded into those clusters, which allowed us to determine the distribution of these facilities amongst the clusters. Finally, knowing how many facilities were present in each cluster and the demographics of each cluster, we were able to determine whether there was an association between certain population characteristics and the location of TRI facilities.

Materials and Methods

Study location

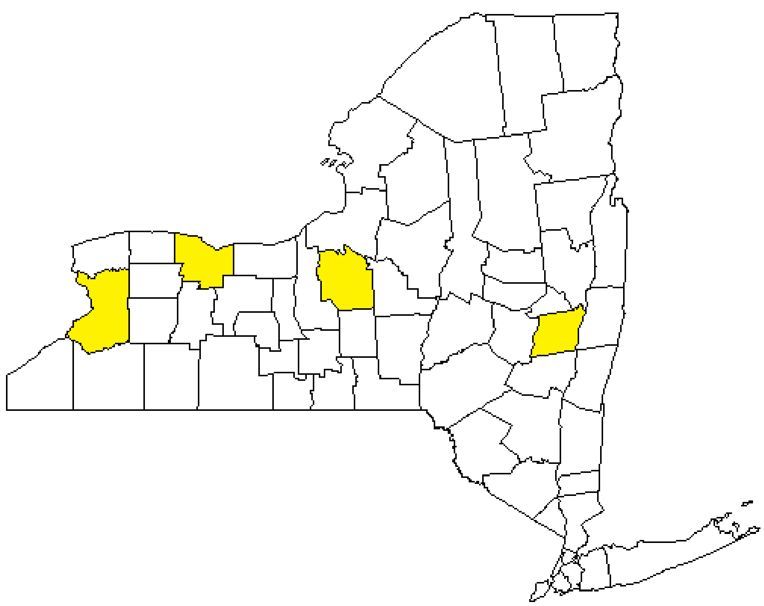

Figure 1. Map of New York State, with (from west to east) Erie, Monroe, Onondaga, and Albany Counties highlighted in yellow

The counties chosen for this study were Erie, Monroe, Onondaga, and Albany Counties, New York. Each of these counties contains a major Upstate New York city and are within 300 miles of one another, forming a line from west to east (Figure 1). Details on each county can be seen below in Table 1.

Table 1. Details of counties

County name	Total land area (square miles)	Total population	Major city	Major city land area (square miles)	Major city population
Erie	1,042.69	950,265	Buffalo	40.38	292,648
Monroe	657.21	735,343	Rochester	35.78	219,766
Onondaga	778.39	458,336	Syracuse	25.04	147,326
Albany	522.80	294,565	Albany	21.39	95,658

(United States Census Bureau, 2019b)

Onondaga County, specifically, was chosen for this study because of the historical presence of polluting facilities and their associated chemical releases. This can be seen particularly around Onondaga Lake, which is a Superfund site. Onondaga Lake covers approximately 4.6 square miles and receives water from a drainage basin of approximately 285 square miles. Chemical disposal has been occurring in the lake for over 125 years; pollution from these operations includes mercury, pesticide and creosotes, heavy metals, and volatile organic compounds (Department of Environmental Conservation, 2010). Onondaga Lake and its related upland sites were added to the Federal Superfund National Priorities List in 1994, as well as the New York State Registry of Inactive Hazardous Waste Disposal Sites (Department of Environmental Conservation, 2010). The ease of comparability between the four counties allowed us a logical means of expansion for this study; therefore, we were able to look at a larger total geographic area while still investigating a similar geographic population.

Defining residential clusters using US Census data

The data used to create our residential clusters was obtained from the 2000 decennial U.S. Census. The Census is considered the largest mobilization and operation conducted in the U.S., requiring years of planning, research, and outreach to ensure as complete of a population count as possible (United States Census Bureau, 2019a). Block groups are the smallest denomination for which social characteristics are reported from the U.S. Census. Block groups are statistical divisions of census tracts, and have relatively small land area and population size, typically only consisting of between 600 and 3,000 people (Lemery, 2019). This small denomination is the most suitable for describing residential characteristics and has been utilized in prior studies (Mirowsky et al., 2017; Weaver et al., 2019). By using these smaller sets of data, we can more accurately cluster residential areas based upon their similar demographics, thereby increasing the study's power.

The 9 variables from the Census chosen for this work can be categorized into seven sub-categories: education, wealth, income, race/ethnicity, employment, housing, and land-use (Mirowsky et al., 2017) (Table 2). These variables are routinely used in studies assessing the health impacts of living in deprived neighborhoods (Ahern et al., 2003; Arora & Cason, 1999; Curry et al., 1993; English et al., 2003; Johnson et al., 2016; Karvonon & Rimpela, 1996; Mirowsky et al., 2017; Reagan & Salsberry, 2005; Roberts, 1997; Wolverton, 2009). For this work, the variables were chosen *a priori*. No sensitivity analysis was performed to try to exclude variables as all attributes were deemed influential. Data from the year 2000 was used because information on the specific variables being studied were not available for the 2010 Census.

For the Race/Ethnicity sub-category, we accounted for the population that identified as any race/ethnicity other than Non-Hispanic White (Arora & Cason, 1999; Roberts, 1997; Hill et al., 2018). Non-Managerial positions were defined as the percentage of both sexes of the employed civilian population 16 years and over in the following: service occupations; sales and office occupations; farming, fishing, and forestry occupations; construction, extraction, and maintenance occupations; and production, transportation, and material moving occupations. The percentage of single parent housing refers to the percentage of male or female only (no spouse present) family households in owner and renter occupied housing divided by the total number of owner and renter occupied housing units. All variable values were expressed as percentages to allow for comparison between block groups and clusters.

Erie, Monroe, Onondaga, and Albany counties were comprised of 913, 601, 409, and 233 block groups, respectively, totaling 2,156 block groups across the four-county area. There were 33 block groups removed from the study due to no population data being available; these block groups were made up of businesses, churches, schools, or parks. This left a total of 2,123 block groups to be examined in this work.

Hierarchical clustering

Hierarchical clustering analysis was done using Ward's hierarchical clustering method (Ward Jr., 1963). The variables were transposed, and the block groups were grouped into clusters based upon similarities in the 9 Census variables. The block groups were spread across all four counties; therefore, block groups within the same cluster were not required to be adjacent to one another. Ward's clustering technique uses a bottom up approach to look for similarities in a group of observations with respect to several variables. By using a bottom up approach, all data points are originally thought of as their own cluster; the two most similar clusters are repeatedly combined, one at a time, to reduce the overall number of clusters being examined. Ward's method was chosen for this analysis because the pooled with-in group sum of squares is minimized, and the cluster distances using Ward's method are defined as the squared Euclidean distance between points (Mirowsky et al., 2017). To determine the optimal number of clusters, the Friedman Method was used (Friedman & Rubin, 1967). The method looks for similarities in the data and based on that information suggests the best possible number of clusters to use.

Toxic Release Inventory (TRI) facilities

The location of every TRI facility (n = 189 facilities) in the four counties in the year 2000 was obtained from TRIExplorer. TRIExplorer is a tool managed by the EPA to share information regarding location, releases, and treatment options used by TRI reporting facilities (United States Environmental Protection Agency, 2020). Five facilities were omitted from this study due to being located in block groups that had no available Census demographic data, leaving 184 TRI facilities to be used for this analysis. The latitude and longitude of each facility was set in the same coordinate system as the residential clusters so the number of facilities per cluster could be determined.

Statistical analysis

Descriptive statistics, at both the county and cluster level, were calculated for each of the 9 Census variables. A linear regression was performed on all the variables against the quantity of facilities present per cluster to determine which variable, if any, had the greatest impact on facility location determination (Supplemental Table 1). Finally, a linear regression was performed on the land area of each residential cluster against the number of facilities present per cluster to determine whether there was a correlation between land area and the number of facilities present. All statistical analyses were done in RStudio (Version 3.5.3) (R Core Team, 2019).

Table 2. US Census variables used to form clusters in analysis

Category	*Variable Details*
Education	Population that has obtained at least a high school diploma
Wealth	Population in owner-occupied housing
Income	Population with income below the poverty line
Race/Ethnicity	Population not identifying as Non-Hispanic White
Employment	Population unemployed
	Population in non-managerial positions
Housing	Single parent housing
	Vacant housing
Land-Use	Urban environment

Results

Formation of and characterization of residential clusters

Starting from 2,123 block groups in Erie, Monroe, Onondaga, and Albany Counties, NY, we used 9 US Census variables to form seven unique residential clusters. When initially performing our analysis using the Friedman method, it was suggested that the optimal number of clusters for our analysis was six. Based on similarities in the data, six was suggested as the optimal number of clusters to use. However, using six clusters, our largest cluster was comprised of 693 block groups, which represents almost a third of the total number of block groups being studied. To minimize the size of this large cluster, we reran our analysis using seven clusters, which broke up this larger cluster into two smaller clusters; therefore, it was determined that seven clusters would be more appropriate for this work. The number of clusters formed is consistent when compared to prior studies using a similar methodology (Humphreys & Carr-Hill, 1991; Mirowsky et al., 2017; Weaver et al., 2019).

The characteristics of each cluster are summarized in Table 3, and a visual representation of the clusters across the 4 counties can be seen in Figure 2. Cluster 1, which contains 411 block groups, represented a high percentage of individuals in non-managerial positions, individuals who were non-white and unemployed, households below the poverty line, and vacant housing. Cluster 2 was made up of 416 block groups and represented a high percentage of individuals who were non-white and working in non-managerial positions; thus, it appears that Clusters 1 and 2 represent the working class. Cluster 4 was comprised of 288 block groups, and represented low percentages of individuals in owner-occupied housing, single parent homes, and non-managerial positions. The 126 block groups making up Cluster 5 were 100% urban and represented the lowest percentage of individuals in owner-occupied housing and the lowest percentage of high school graduates. This cluster also represented the highest percentage of single parent households, non-White individuals, unemployment, individuals working in non-managerial positions, households below the poverty line, and vacant housing. Cluster 7 was made up of 189 block groups, was highly rural, and represented a high percentage of individuals living in owner-occupied housing, and a low percentage of households below the poverty line.

Clusters 6 and 3 appeared to be almost identical in characteristics, with a small difference between the percentage of high school graduates and a large difference between the percentage of non-managerial positions in the clusters. This similarity is due to the large, 693 block groups cluster splitting into two smaller clusters when we changed our overall number of clusters from six to seven. There were 333 block groups that made up Cluster 3, which represented the highest percentage of high school graduates and owner-occupied housing, and the lowest percentage of single parent households, unemployed individuals, individuals in non-managerial positions, and households below the poverty line. Cluster 6 was made up of 360 block groups and had a high percentage of individuals who were Non-Hispanic White and lived in owner-occupied housing. Looking at Figure 2, Cluster 3 and Cluster 6 are typically very separated; for instance, in Monroe county almost all the block groups in Cluster 3 are in the east, and almost all the block groups in Cluster 6 are in the west. This separation is seen for every county except Onondaga County, where the two clusters appear to be intermingled. However, Cluster 6 always appears to be located closer to TRI facilities than Cluster 3.

Table 3. Summary of cluster characteristics

	Total*	**Cluster 1**	**Cluster 2**	**Cluster 3**	**Cluster 4**	**Cluster 5**	**Cluster 6**	**Cluster 7**
	n = 2123 BGs	**n = 411 BGs**	**n = 416 BGs**	**n = 333 BGs**	**n = 288 BGs**	**n = 126 BGs**	**n = 360 BGs**	**n = 189 BGs**
Land area (square miles)	**2992.16**	**81.12**	**195.01**	**355.75**	**109.07**	**12.24**	**282.85**	**1956.12**
Number of facilities	**184**	**58**	**60**	**6**	**19**	**8**	**17**	**16**
High school graduates (%)	82 ± 13	69 ± 11	80 ± 8	94 ± 5	86 ± 9	57 ± 12	89 ± 4	89 ± 5
Owner occupied housing (%)	63 ± 27	42 ± 18	66 ± 15	86 ± 13	37 ± 20	25 ± 14	86 ± 10	86 ± 10
Single parent household (%)	19 ± 13	32 ± 12	18 ± 7	9 ± 4	14 ± 7	45 ± 14	12 ± 5	11 ± 5
Other race (%)	24 ± 30	64 ± 29	9 ± 9	8 ± 7	21 ± 15	82 ± 18	5 ± 5	4 ± 5
Unemployed (%)	4 ± 4	6 ± 4	4 ± 3	2 ± 1	3 ± 3	14 ± 8	2 ± 2	3 ± 2
Non-managerial position (%)	66 ± 16	79 ± 10	75 ± 9	43 ± 9	56 ± 10	84 ± 10	64 ± 7	63 ± 11
Below poverty line (%)	14 ± 15	28 ± 11	10 ± 7	3 ± 3	16 ± 14	50 ± 12	4 ± 3	4 ± 3
Urban (%)	92 ± 25	98 ± 12	100 ± 1	97 ± 9	100 ± 2	100 ± 0	100 ± 2	18 ± 22
Vacant (%)	9 ± 9	18 ± 10	7 ± 5	3 ± 3	7 ± 6	22 ± 11	3 ± 2	6 ± 8

**The Total column is the average of each parameter across all seven clusters.*

Residential clusters and TRI facility location

The location of the TRI facilities was overlaid onto the county cluster maps (Figure 2), and the number of the polluting facilities per cluster (and per cluster per county) was calculated. Not all the clusters in each county had a TRI facility present. For example, in both Albany and

Onondaga counties, there are no TRI facilities present in Cluster 5; however, there are facilities in Cluster 5 in both Erie and Monroe counties.

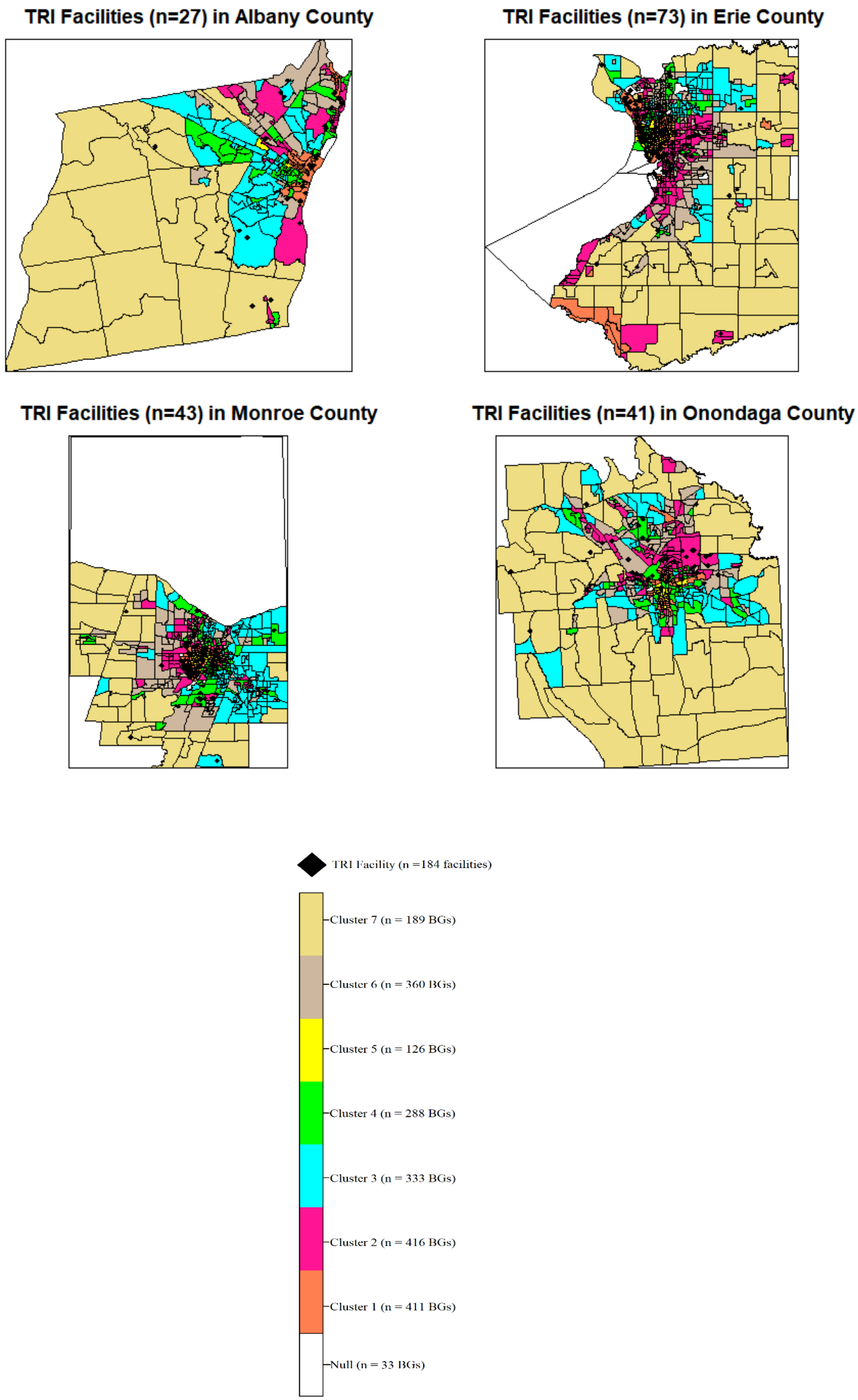
TRI Facilities (n=27) in Albany County
TRI Facilities (n=73) in Erie County
TRI Facilities (n=43) in Monroe County
TRI Facilities (n=41) in Onondaga County
TRI Facility (n =184 facilities)
Cluster 7 (n = 189 BGs)
Cluster 6 (n = 360 BGs)
Cluster 5 (n = 126 BGs)
Cluster 4 (n = 288 BGs)
Cluster 3 (n = 333 BGs)
Cluster 2 (n = 416 BGs)
Cluster 1 (n = 411 BGs)
Null (n = 33 BGs)

Figure 2. Location of 184 Toxic Release Inventory (TRI) facilities within seven characteristically similar residential clusters comprised of 2,123 Census block groups in Albany, Erie, Monroe, and Onondaga Counties. 33 block groups having partial or no population were removed and are labeled as "Null".

A total of 184 TRI facilities were in our four-county area. Erie County, the largest of the counties studied, had the most TRI facilities (n = 73). In Erie County, the most TRI facilities were found in Cluster 1, where 33 TRI facilities were present. Albany county, the smallest of the four counties studied, had the least amount of TRI facilities (n = 27). In Albany County, the most TRI facilities were found in Cluster 2, where 10 TRI facilities were located. Overall, the greatest number of facilities (n=60) were found in Cluster 2 (Table 4) which was the cluster with the most block groups (n=416), but the fourth largest (n=195.01 square miles) land area (Table 3). The least number of facilities (n=6) were found in Cluster 3 (Table 4) which had the fourth smallest amount of block groups (n=333), but the second greatest land area (n=355.75 square miles) of all the clusters (Table 3).

In Figure 2, there are specific residential clusters that appear to be interwoven with one another. This can be seen with Clusters 1 and 5; Clusters 2 and 6; and Clusters 3 and 4. Cluster 5, which is 100% urban, represents the major downtown areas and appears to be surrounded by Cluster 1, which is 99% urban. These interwoven clusters appear to form rings, branching out from the major urban city. Cluster 1 block groups are located within the major city lines, but not necessarily in the downtown areas, showing a slight transition to a more suburban neighborhood. Clusters 3 and 4 appeared to be intermingled, while also surrounding Clusters 1 and 5. Cluster 4 is 100% urban and is more closely located to the major downtown areas than Cluster 3, which is 97% urban. Clusters 3 and 4 don't share many similar demographics but are close in their percentages of workers in non-managerial positions. Cluster 3 has the lowest percentage of workers in non-managerial positions, 43%, and Cluster 4 has the second lowest percentage of workers in non-managerial positions, 56%. Clusters 2 and 6 appear to be intermingled and surrounding Clusters 3 and 4. Cluster 2, which is 100% urban, is typically located closer to the downtown area than Cluster 6, which is 100% urban. The two clusters have some similar demographic characteristics, such as their Race/Ethnicity makeup; Cluster 2 is 9% Other Race while Cluster 6 is 5% Other Race. Cluster 2 is also comprised of 75% workers in non-managerial positions with Cluster 6 closely related at 64% workers in non-managerial positions. Cluster 7 block groups were located on the outskirts of the counties, surrounding the portion of the county not being taken up by the major cities. This cluster was also the least urban.

Overall, it was determined that the working-class population are the most likely group to be proximate to TRI facilities. Looking at Clusters 1 and 2, we saw two of the highest percentages of people working in non-managerial positions; these two clusters also had the two highest amounts of facilities located within them (Table 3). A linear regression was performed on all variables tested to find the correlation between the number of facilities present in the cluster and each variable. Looking for trends in the data, we found that the regression between those working in non-managerial positions and the number of facilities present was $R^2 = 0.25$ with a p-value of 0.26. The relationship was found to be not significant, but it was the highest correlation of all parameters (Supplemental Table 1).

The total amount of chemicals released in our four-county area in the air, water, and on land was 17 million pounds. Monroe County, which is the second smallest of the four counties (Table 1) being studied, released the most chemicals, totaling 6.9 million pounds (Supplemental Table 4). The county releasing the least amount of chemicals was Albany county, which is the smallest county studied (Supplemental Table 2). The largest quantity of chemicals was released throughout Cluster 2, where 6 million pounds of chemical releases occurred. The smallest quantity of chemicals released was in Cluster 5 (Table 4). Cluster 5 had the second smallest amount of TRI facilities (n=8) and the lowest (n=12.24 square miles) land area (Table 3).

Table 4. Number of TRI facilities per cluster broken down by county and releases

Cluster	Albany	Erie	Monroe	Onondaga	Total # of facilities per cluster	Quantity of on-site releases (Pounds)	% of on-site releases
1	7	33	14	4	58	5,331,191	31%
2	10	21	10	19	60	6,038,179	36%
3	3	1	2	0	6	395,285	2%
4	2	2	9	6	19	1,799,524	11%
5	0	4	4	0	8	10,043	<1%
6	2	6	2	7	17	475,652	3%
7	3	6	2	5	16	2,970,262	17%
Total	27	73	43	41	184	17,020,136	100%

Source: (United States Environmental Protection Agency, 2020)

*On-site releases are the total releases from air, water, and land.

A linear regression was performed between the area of each cluster and the number of facilities per cluster to assess if it is possible that, due to a larger geographical area, more facilities would be present. The regression value showed no correlation ($R^2 = 0.054$).

Discussion

In this study, we utilized a hierarchal clustering method to explore how residential socioeconomic status (R-SES) is distributed across four counties located in Upstate New York. For our analysis, we aggregated 2,123 US Census block groups across Erie, Monroe, Onondaga, and Albany Counties into seven unique clusters based upon 9 R-SES demographic factors. We then assessed whether the location of the TRI facilities disproportionately influenced specific demographic groups living close to them. While there is a large body of evidence suggesting that areas with higher percentages of minorities and low-income individuals are exposed to greater quantities of polluting facilities, our results did not support those other works. Rather, we found that the greatest quantity of facilities appeared in Clusters 1 and 2, both of which had very high percentages of employees working in non-managerial positions (Table 3).

The environmental justice literature on residential SES and hazardous waste facilities is diverse; an extensive review was performed in order to determine the variables most appropriate for assessing area-level SES. Education level has been a factor used in multiple studies assessing area-level SES and health (Ahern et al., 2003; Arora & Cason, 1999; Curry et al., 1993; English et al., 2003; Evans & Marcynyszyn, 2004; Johnson et al., 2016; Karvonon & Rimpela, 1996; Mirowsky et al., 2017; Pastor Jr. et al., 2001; Reagan & Salsberry, 2005; Roberts, 1997; Wolverton, 2009). The geographical areas chosen for this study include many colleges and universities, so we selected high school graduation as our associated variable for this sub-category. The volume of universities and colleges also lead to the decision of looking at owner occupied housing (Arora & Cason, 1999; Mirowsky et al., 2017; Pastor et al., 2001; Wolverton, 2009) as opposed to median home value. This separates renters from owners, as we would expect to see in many university neighborhoods (Mirowsky et al., 2017). From the perspective of the facilities and siting, we looked at poverty levels (Ahern et al., 2003; Arora & Cason, 1999; Evans & Marcynyszyn, 2004; Johnson et al., 2016; Mirowsky et al., 2017; Reagan & Salsberry, 2005; Roberts, 1997; Wolverton, 2009) and vacant housing (Arora & Cason, 1999; Johnson et al., 2016; Mirowsky et al., 2017; Reagan & Salsberry, 2005; Wolverton, 2009). With vacant housing, if firms are paying out compensation to all individual members of a community for placing a facility within the community, it has been speculated that they will look at the amount of people living in the neighborhood, as well as the amount of vacant housing present

(Wolverton, 2009). More vacant housing in a neighborhood potentially means less people in the neighborhood, so less money is paid out in compensation to individuals overall (Wolverton, 2009). For labor occupation, we were specifically looking at the percent of the population in non-managerial positions, again consistent with prior work (Ahern et al., 2003; Arora & Cason, 1999; English et al., 2003; Karvonon & Rimpela, 1996; Mirowsky et al., 2017; Pastor Jr. et al., 2001; Roberts, 1997; Wolverton, 2009). Other metrics such as single parent households (English et al., 2003; Evans & Marcynyszyn, 2004; Karvonon & Rimpela, 1996; Mirowsky et al., 2017; Pastor Jr. et al., 2001; Reagan & Salsberry, 2005; Roberts, 1997), race (Ahern et al., 2003; Arora & Cason, 1999; Curry et al., 1993; English et al., 2003; Evans & Marcynyszyn, 2004; Johnson et al., 2016; Mirowsky et al., 2017; Pastor Jr. et al., 2001; Reagan & Salsberry, 2005; Roberts, 1997; Wolverton, 2009), unemployment (Ahern et al., 2003; Arora & Cason, 1999; Curry et al., 1993; Mirowsky et al., 2017; Roberts, 1997; Wolverton, 2009), and percent urban (Arora & Cason, 1999; Curry et al., 1993; English et al., 2003; Evans & Marcynyszyn, 2004; Mirowsky et al., 2017; Wolverton, 2009) have been used extensively in the literature by other researchers when assessing R-SES.

There are many studies citing race and income as two of the most important variables in terms of disproportionate exposure or placement location of hazardous waste facilities (Bullard et al., 2007; Commission for Racial Justice, 1987; Elliott et al., 2004; Jenkins et al., 2004; Johnson et al., 2016; Mohai et al., 2009; Mohai & Saha, 2007; Pastor Jr. et al., 2001; Perlin et al., 1995; Zimmerman, 1993). While we did utilize a different, more novel method, our results appear to show a different trend. Cluster 5 has the highest percentages of minorities and households below the poverty line. However, the cluster only has 8 TRI facilities, compared to Cluster 2, which has 60 TRI facilities, and relatively low percentages of minorities and households below the poverty line. While, it is possible that the urban areas being studied in this work did not have the adequate space for building larger, polluting factories, we did look at whether there was a correlation between land area and number of facilities present. We found no such correlation to exist ($R^2 = 0.0541$). Instead, we found that the variable that appeared to be most influential in where these facilities are sited, of those chosen, was the percent of the population in non-managerial positions. For Clusters 1 and 2 – the clusters with the most TRI facilities within them – there was a higher than average percentage of workers in non-managerial positions. In addition, for Cluster 3, which was the cluster with the fewest number of TRI facilities, there was a smaller percentage of workers in non-managerial positions. These findings support the thought that, when siting potential locations for facilities, the ease with which a plant can hire workers, and the qualifications of those workers, is taken into consideration. Firms will often prefer a location that provides access to a large pool of inexpensive, available workers (Ringquist, 1997; Wolverton, 2009). Similar results to ours have been seen across other, similar studies (Boer et al., 1997; Cutter et al., 2002; Kriesel et al., 1996; Ringquist, 1997). Additionally, we were able to determine that 67% of chemical releases across the four counties occurred in Clusters 1 and 2 (Table 4). This shows that workers in non-managerial positions are also more likely to be exposed to chemical releases and pollutants.

The present study has several limitations. First, the data used in this study were from 2000; this was because there was no block group demographic data available in 2010. Next, the clusters created in this study are very specific to the variables we chose. Unfortunately, the literature on this subject is so diverse that there is no consensus as to what the best variables to describe R-SES would be (Messer et al., 2006). However, we included many of the most commonly utilized variables from prior studies. There are also several limitations associated with the TRI data. First, the minimum reporting requirements of the TRI program reduces the amount of facilities that must report; this means that many smaller facilities, such as autobody shops, are not required to report to the TRI program (Dolinoy & Miranda, 2004; United States Environmental Protection Agency, 2019b; Wilson et al., 2012). Next, the TRI program does not address the environmental fate or transport of industry emissions. In our study, this could greatly influence which clusters are being exposed to higher quantities of pollutants, especially if the facilities are located near the border of different block groups. Additionally, while the TRI program does report the quantity of chemicals released, just addressing the quantity of chemicals released isn't a sufficient method of determining potential environmental exposure (Toffel & Marshall, 2004). Finally, this study did not address the SES of the clusters at the time the facilities were being sited, but rather looked at them concurrently. While not necessarily noted as such, this is a major limitation in several other studies that take demographic data from one specific year as opposed to a time series or the year a facility was sited (Dolinoy & Miranda, 2004; Neumann et al., 1998; Wilson et al., 2012). Therefore, we cannot determine whether these neighborhoods existed prior to building the facilities, or whether the facilities brought workers into the surrounding neighborhoods. This is a common issue in the EJ field and is known as the chicken and the egg debate (Mohai et al., 2009). One important study by Pastor et al. (2001) stated that, over a 30-year period, toxic facilities tended to be located in vulnerable neighborhoods, not the other way around. However, the siting and founding dates of these facilities are not noted on the public R-forms released by facilities and are, therefore, difficult to acquire. Thus, the objective of this study was to assess which populations were most at risk from polluting facilities being in their neighborhoods and not assess how this situation occurred.

There are several strengths from this study that should be recognized. First, this study used hierarchal clustering to form the geographical neighborhoods. Clustering is a more novel technique to examine R-SES, used in only a handful of studies (Humphreys & Carr-Hill, 1991; Mirowsky et al., 2017; Weaver et al., 2019). Many studies focusing on R-SES use principal components analysis (PCA), typically followed by the development of a neighborhood deprivation index (NDI) or z-score (Berkowitz et al., 2015; English et al., 2003; Feldman & Steptoe, 2004; Humphreys & Carr-Hill, 1991; Jones & Duncan, 1995; Messer et al., 2010; Pampalon et al., 2012). Our analysis lets us utilize all the demographic indicators we assume to be important in our analysis, rather than mathematically reducing that number of indicators using statistical techniques. Next, this study utilized US Census block groups. Some studies have been performed to determine the appropriate geographic scale for area-level SES disparities and have found scaling to be one of the most important factors in this type of analysis (Dolinoy & Miranda, 2004; Perlin et al., 1995). Block groups are a smaller geographic area than census tracts, but there are more studies assessing R-SES done at the census tract level (Ahern et al., 2003; Berkowitz et al., 2015; Cutter et al., 1996; Dolinoy & Miranda, 2004; Reagan & Salsberry, 2005; Sadd et al., 1999; Wilson et al., 2012; Yandle & Burton, 1996) than at the block group level (Berkowitz et al., 2015; Cutter et al., 1996; Dolinoy & Miranda, 2004; Mirowsky et al., 2017; Weaver et al., 2019). Finally, our study looked at both the location of these TRI facilities, and the quantity of their emissions. Some prior work neglected looking at emissions from facilities concurrently with their examination into the location of the facilities (Cutter et al., 1996; Wilson et al., 2012) as to focus on just the demographics surrounding hazardous waste facilities. To truly examine the burden of TRI facilities, we decided to include basic emission levels in this study. This practice has been demonstrated by other studies (Bullard, 1996;

Dolinoy & Miranda, 2004; Neumann et al., 1998; Ringquist, 1997) and allows for an in-depth analysis of not just the location of these facilities, but also the amount of chemicals they're releasing into their surrounding areas.

Conclusions

In conclusion, we used hierarchical clustering to identify seven unique residential clusters in Albany, Erie, Monroe, and Onondaga Counties based on 9 US Census demographic variables. Our study was conducted at the block group level, which is one of the smallest land designations offered by the US Census. Using Toxic Release Inventory (TRI) data, we were able to identify all facilities within these four counties and show a relationship between the residential cluster characteristics and the location of these TRI facilities. The characteristic that seemed to be most influential in the location of these facilities was the percent of the population in non-managerial positions. These positions provide a proximity to work for the employee, and skilled, available labor for the employer. No clear relationship between race and income with the presence of TRI facilities was seen.

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Supplemental Information

Supplemental Table 1. Linear regression coefficients

	HSG	OOH	SPH	OR	UnE	NMP	BPL	Urb	Vac
R^2	0.0493	0.0284	0.0272	0.0088	0.0039	0.2452	0.0005	0.0415	0.0306

Abbreviations: HSG, High School Graduate; OOH, Owner Occupied Housing; SPH, Single Parent Housing; OR, Other Race; UnE, Unemployed; NMP, Non-Managerial Positions; BPL, Below Poverty Line; Urb, Urban; Vac, Vacant Housing

Supplemental Table 2. Albany county releases (pounds)

Cluster	Total (lbs)	Air Releases (lbs)	Water Releases (lbs)	Land Releases (lbs)
1	23,398	23,373	25	0
2	163,993	150,110	13,878	5
3	394,750	364,498	30,252	0
4	2094	2,094	0	0
5	--	--	--	--
6	21,550	21,550	0	0
7	88,995	88,969	0	0
Total	694,749	650,594	44,155	5

Supplemental Table 3. Erie county releases (pounds)

Cluster	Total (lbs)	Air Releases (lbs)	Water Releases (lbs)	Land Releases (lbs)
1	4,897,371	4,675,838	221,533	0
2	153,306	124,635	28,671	0
3	0	0	0	0
4	1	1	0	0
5	110	110	0	0
6	360,488	360,488	0	0
7	46,644	46,644	0	0
Total	5,457,920	5,207,716	250,204	0

Supplemental Table 4. Monroe county releases (pounds)

Cluster	Total (lbs)	Air Releases (lbs)	Water Releases (lbs)	Land Releases (lbs)
1	124,876	124,876	0	0
2	5,043,355	4,361,208	682,030	116
3	535	520	15	0
4	1,786,278	1,786,236	42	0
5	9,933	9,933	0	0
6	8,001	8,001	0	0
7	3,369	3,308	61	0
Total	6,976,346	6,294,082	682,148	116

Supplemental Table 5. Onondaga county releases (pounds)

Cluster	Total (lbs)	Air Releases (lbs)	Water Releases (lbs)	Land Releases (lbs)
1	285,536	285,536	0	0
2	677,524	677,427	92	5
3	--	--	--	--
4	11,152	10,902	250	0
5	--	--	--	--
6	85,613	64,654	20,909	50
7	2,831,254	33,350	2,797,904	0
Total	3,891,079	1,071,869	2,819,155	55

CHAPTER 3: ASSSESSING THE RELATIONSHIP BETWEEN NEIGHBORHOOD SOCIOECONOMIC STATUS AND TOXIC CHEMICAL RELEASES IN UPSTATE NEW YORK

Abstract

It has previously been demonstrated that certain demographic groups – particularly minorities and low-income individuals – live disproportionately closer to polluting facilities. Therefore, we investigated the chemical releases from Toxic Release Inventory (TRI) facilities in four comparable counties in Upstate New York (Albany, Erie, Monroe, and Onondaga Counties). The chemicals released were weighted based upon their potential toxicity to determine if any demographic group could be at increased odds of exposure to more hazardous chemicals. Using hierarchal clustering, we created seven unique residential clusters made from nine population demographics representing neighborhood-based socioeconomic status. We then geocoded the location of polluting facilities using EPA's Toxic Release Inventory (TRI) to determine which residential cluster each facility was located in. The quantity, in pounds, of chemicals released was calculated, and then the Facility Scores from EPA's Risk-Screening Environmental Indicators (RSEI) Model were obtained. The top five facilities with the highest Facility Scores per cluster were examined in more detail. Three clusters, Clusters 1, 2, and 6, had Facility Scores that were consistently greater than the Facility Scores in the other clusters. Looking at the demographics of Clusters 1, 2, and 6, we found that the groups potentially most affected by more toxic chemicals were those working in non-managerial positions and those without a high school degree. However, when we assessed the quantity of chemicals released in these clusters, Clusters 1 and 2 had the two highest quantities of chemicals released, and Cluster 6 had one of the lowest quantities of chemicals released, suggesting that using the quantity of chemicals

released alone may be misleading in terms of potential toxicity and exposure. This also suggests that communities that have TRI facilities that report minimal quantities of chemical releases may be at the same level of risk of pollutant exposure as the communities that have TRI facilities reporting large quantities of chemical releases.

Introduction

In 1984, a leak of methylisocyanate occurred at the Union Carbide Limited pesticide plant in Bhopal, India (United States Environmental Protection Agency, 2019b). This leak resulted in injury, or death, of at least 2,000 people. Due to fears of a similar incident occurring, a pivotal piece of legislature, The Emergency Planning and Community Right-to-Know Act (EPCRA), was put into place in the United States. EPRCA requires federal, state, and local governments; tribes; and industries to have emergency response plans set in place in case another incident like Bhopal were to occur. One of the sections within this act established the Toxic Release Inventory (TRI) program. The TRI program tracks the management of over 650 chemicals across the United States; the facilities that release these chemicals are known as TRI facilities. The identity and quantity of chemicals released by each facility is recorded in a public database every year (United States Environmental Protection Agency, 2019c).

Prior work has found that TRI facilities and other hazardous waste sites are located in areas with high concentrations of minorities and low-income individuals (Ash & Fetter, 2002; Bouwes et al., 2001; Chakraborty, 2009; Commission for Racial Justice, 1987; Downey & Hawkins, 2008; Pastor et al., 2005; Perlin et al., 1995; Sicotte, 2010; Sicotte & Swanson, 2007; Williams, 2008). There are several possible reasons for these findings. One study suggested that inexpensive industrial land draws in low-income families due to the low price of the land, and the racial explanations fall back on deliberate discrimination, white privilege, and structural racism (Sicotte, 2010). Other researchers have found different variables, such as the amount of people working in non-managerial positions, to also be influential in where a facility is sited (Been, 1995; Brulle & Pellow, 2006; Cutter et al., 1996; Pastor et al., 2005; Ringquist, 1997; Williams, 2008). In the study done by Ringquist (1997), he stated that the economic factors most relevant to TRI facility locations are cheap land, available skilled labor, and access to transportation infrastructure. Other variables, such as the presence of vacant housing units (Sicotte, 2010), the lack of a high school diploma (Sicotte, 2010), high levels of unemployment (Bouwes et al., 2001), and a decrease in home ownership (Pastor et al., 2005), have also been cited as more prevalent in areas with higher exposure and proximity to polluting TRI facilities.

Studies utilizing population demographics often use variables addressing both neighborhood- and individual-level socioeconomic status (SES). SES variables are often ranked in other studies from worst to best, describing some neighborhoods as having lower SES and some neighborhoods as having higher SES (Diez Roux et al., 2001; Messer et al., 2010; Reagan & Salsberry, 2005). Neighborhoods comprised of more TRI facilities are often described as having lower SES and are often comprised of high levels of minorities and low-income households (Wilson et al., 2012).

When looking at TRI facilities, it is advantageous to look at not just the placement of the facility, but also the quantity of chemical releases emanating from the facility. It is important, however, to recognize that analyzing just the quantity of chemicals released may not be an accurate way to measure environmental exposure to chemicals (Toffel & Marshall, 2004). One study noted that the human health impacts of carcinogens vs. non-carcinogens can differ by up to seven or eight orders of magnitude (Abel, 2008; Bouwes et al., 2001). This suggests that the specific chemical itself, rather than its quantity, might be more important when discussing potential human health effects. To address the differences in the quantity of chemicals released and their associated toxicity the Risk-Screening Environmental Indicators (RSEI) model could be utilized.

RSEI is a multi-media model that analyzes the quantity of chemicals released from facilities along with other risk factors, such as the chemical's fate in the environment and its relative toxicity (United States Environmental Protection Agency, 2017a). The RSEI model works directly with the TRI program by incorporating over 30 years of TRI chemical release data along with data from three U.S. Censuses, the toxicity and physical properties of most TRI chemicals, and the geographic information of TRI facilities and water bodies. This information is used to model the route of each chemical through the environment along with the potential human exposure that could result (United States Environmental Protection Agency, 2017a).

The objective of this study was to determine if any demographic groups were disproportionately exposed to toxic chemicals released from TRI facilities in Upstate New York. In our analysis, we utilized a clustering technique to form seven unique residential clusters within four Upstate New York counties. The TRI facilities within our four-county study area that had an EPA-provided Facility Score were then geocoded within these clusters. The quantity of chemicals released was determined for each cluster, the Facility Scores were generated from the EPA's RSEI database, and the top five facilities per cluster with the highest Facility Scores were assessed in greater detail. The clusters that appeared most affected were then examined for similar population demographics to explore whether certain population characteristics were more prominent amongst the most affected clusters.

Materials and Methods

Study location

Four counties in Upstate New York (Erie, Monroe, Onondaga, and Albany) were used in this study. Each county contains a major Upstate New York city, with Buffalo found in Erie County, Rochester in Monroe County, Syracuse in Onondaga County, and Albany, the state capital of New York, in Albany County. All four counties are comparable due to their geographic location in Upstate New York, similar land size, and presence of a major Upstate city. More data on county and city size can be seen in Supplemental Table 1. The populations of these four counties differ greatly, ranging from 951,000 people in Erie County to 295,000 people in Albany County; however, each major city housed approximately 30% of each county's total population (United States Census Bureau, 2019).

Using US Census data to define residential clusters

This research utilized block group data from the 2000 decennial U.S. Census representing nine different demographic variables. There currently is no standard index to use for studies assessing neighborhood-associated socioeconomic status; however, there are subcategories that have been listed as influential in describing a neighborhood (Messer et al., 2006). Within these subcategories, we sought out variables that have been highly utilized in past work (Messer et al., 2006, 2010; Mirowsky et al., 2017; Reagan & Salsberry, 2005; Roberts, 1997; Weaver et al., 2019). The seven subcategories utilized in this study are education, wealth, income, race/ethnicity, employment, housing, and land-use; all variables within the subcategories were expressed as percentages for comparison. The variables utilized in this study included, high school graduates (education), living in owner-occupied housing (wealth), population with income below the poverty line (income), population not identifying as Non-Hispanic White (race/ethnicity), population unemployed (employment), population holding non-managerial positions (employment), single parent households (housing), vacant housing (housing), and urban land area (land-use).

Within the Race/Ethnicity category, we looked at the percent of the population reporting to the Census that did not identify as Non-Hispanic White; this includes Hispanic and Non-Hispanic African Americans, American Indian and Alaska Natives, Asians, native Hawaiian and other Pacific Islander, and other races. The non-managerial variable was defined as the percentage of both males and females of the employed civilian population 16 years and over in all occupations other than those designated as management, professional, and related occupations. Finally, the single parent household variable referred to the percentage of male or female only (no spouse present) family households in owner or renter occupied housing.

The four counties, Erie, Monroe, Onondaga, and Albany were comprised of 913, 601, 409, and 233 block groups, respectively; this totaled 2,156 block groups. However, 33 block groups contained no population data and were removed from the analysis. The left us with a 2,123 block groups to be analyzed for this work.

Hierarchical clustering techniques

Ward's hierarchical clustering method was used in this study to aggregate our nine Census variables into neighborhood clusters based upon similarities between our block groups (Ward Jr., 1963). As our study area was spread across four counties, the block groups within the formed clusters were not required to be adjacent to one another. Ward's method, which uses a bottom up approach to look for similarities in a group of observations with respect to multiple variables, has been used by other studies to assess neighborhood socioeconomic status

(Mirowsky et al., 2017; Weaver et al., 2019). To determine the optimal number of clusters for this analysis, the Friedman method was also utilized (Friedman & Rubin, 1967).

Toxic Release Inventory (TRI) facilities

The location and emissions data of all TRI facilities (n = 189 facilities) in our four-county study area were collected from the TRIExplorer tool from the year 2000 to be consistent with the Census data we used. TRIExplorer is a tool managed by the EPA that can be used to obtain information about a TRI facility's location, chemical releases, and treatment options (including on-site and off-site treatment) (United States Environmental Protection Agency, 2020a). Five facilities were in block groups that had been previously excluded due to a lack of population data, leaving 184 TRI facilities to be examined. The facilities were geocoded into the residential clusters, and the number of facilities per cluster was determined. The chemical release emissions and the quantity of carcinogenic chemicals released per cluster were calculated. Chemical release emissions were calculated by summing the total on-site releases of each chemical from each facility, and the quantity of carcinogenic chemical releases per cluster was calculated by adding up the quantity of on-site releases of only the chemicals classified as carcinogenic.

Risk-Screening Environmental Indicators RSEI data and calculations

Using the Risk-Screening Environmental Indicators (RSEI) model, the toxicity of each chemical released by a facility can be used to calculate three general scores: RSEI Hazard Score, RSEI Modeled Hazard Score, and RSEI Score. An overall Facility Score for each TRI facility can also be calculated. The specifics to calculate each score can be seen in Table 1.

Table 1. Calculating RSEI values

Score	How to calculate
RSEI Score	Estimated dose (media-specific modeling) x toxicity weight x number of potentially exposed people
RSEI Hazard Score	Quantity of Chemicals (pounds) x toxicity weight of chemical
RSEI Modeled Hazard Score	Quantity of Chemicals (pounds) x toxicity weight of chemical *(does not consider all media)
RSEI Facility Score	Summation of either all RSEI Scores, RSEI Hazard Scores, or RSEI Modeled Hazard Scores for chemicals released by a facility

Source: (United States Environmental Protection Agency, 2017b)

The difference between a RSEI Hazard Score and a RSEI Modeled Hazard Score is that using the term RSEI Modeled Hazard Score emphasizes that not every possible release or transfer is included in the calculation. RSEI Modeled Hazard Scores are often less than RSEI Hazard Scores because not all media (on-site releases, off-site releases, transfers, etc.) is included (United States Environmental Protection Agency, 2017b). The scores for each chemical a facility releases can then be added together to obtain a Facility Score (United States Environmental Protection Agency, 2017c); however, you can only combine like scores. For example, you can’t combine a RSEI Hazard Score with a RSEI Score because they consider different variables. Moreover, RSEI values are only meaningful in comparison to other RSEI values (United States Environmental Protection Agency, 2017a, 2017d).

For this study, we obtained Facility Scores from the EPA’s website for TRI facilities that had catalogued on-site releases. On-site releases include stack and fugitive air releases; water releases; class I, class II, RCRA C, and other landfills; land treatment and application; surface impoundment; and other disposal (United States Environmental Protection Agency, n.d.). Of the 184 TRI facilities in our study area, 55 facilities did not have EPA-generated Facility Scores and were removed from the study leaving 129 TRI facilities for our analysis (Horvath et al., 1995). Of those 129 facilities, the top five facilities with the highest Facility Scores per cluster were chosen to have their chemical releases more closely scrutinized. We chose the top five facilities because we were looking to address the top polluters in the clusters.

Statistical Analysis

Pearson correlation coefficients were calculated between the 9 selected Census variables before clustering to ensure none of the variables were too highly correlated; these results can be seen in Supplemental Figure 1. All statistical analyses were done in RStudio (Version 3.5.3) (R Core Team, 2019).

Results

Overall Facility Separation

For our study, we first were interested in looking at how the 129 TRI facilities were dispersed across the geographical area being studied. The results of that analysis can be seen in Table 2. Most of the TRI facilities were present in Erie County (n = 54). This was followed by Monroe County having 32 facilities, Onondaga County having 28 facilities, and Albany County having only 15 facilities present. When looking at the clusters, Clusters 1 (n = 46) and 2 (n = 44) have the highest amount of facilities within them whereas Clusters 3 (n = 3) and 5 (n = 5) have the fewest (Table 2).

Table 2. Overall Facility Breakdown

Cluster	Albany	Erie	Monroe	Onondaga	Total
1	4	29	10	3	46
2	6	17	8	13	44
3	2	0	1	0	3
4	1	1	7	3	12
5	0	1	3	0	4
6	1	4	2	5	12
7	1	2	1	4	8
Total	15	54	32	28	129

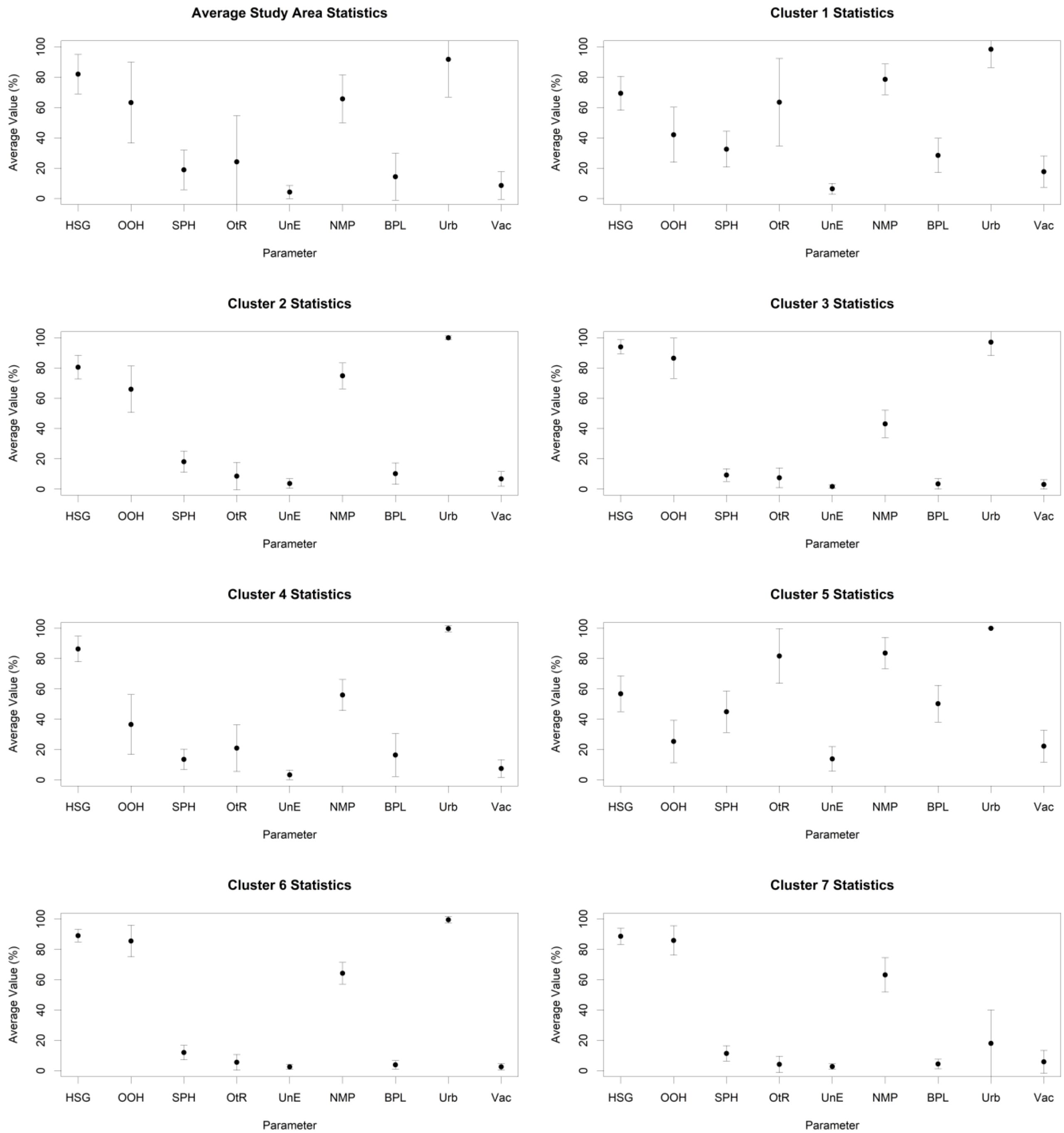


Figure 1. Breakdown of the demographics of each cluster. The 'Average Study Area Statistics' plot is the average of each demographic across all seven clusters. Abbreviations: HSG, high school graduate; OOH, owner occupied housing; SPH, single parent household; OtR, other race;

UnE, unemployed; NMP, non-managerial position; BPL, below poverty line; Urb, urban; Vac, vacant housing

Using Ward's method of hierarchal clustering, we produced seven unique residential clusters. The average of each demographic per cluster and the overall average of each demographic in our four-county study area was calculated (Figure 1). The percentage of high school graduates was highest in Clusters 3 and 6, and lowest in Clusters 1 and 5. Clusters 3 and 7 had high percentages of owner-occupied housing whereas Clusters 1 and 5 had low levels of owner-occupied housing. The lowest levels of single parent households were in Clusters 3 and 7, and the highest levels were in Clusters 1 and 5. Clusters 6 and 7 had the lowest percentages of residents not identifying as Non-Hispanic White and Clusters 1 and 5 had the highest levels. Unemployment was the lowest in Clusters 3 and 6 and was the highest in Clusters 1 and 5. The percentage of those working in non-managerial positions was lowest in Clusters 3 and 4, and highest in Clusters 1 and 5. The percentage of those living in poverty was lowest in Clusters 3 and 6, and was highest in Clusters 1 and 5. The percent of Urban land was lowest in Clusters 3 and 7, and highest in Clusters 2 and 5. Finally, Clusters 3 and 6 had the lowest percentage of vacant housing and Clusters 1 and 5 had the highest percentage (Figure 1).

Table 3. Top 5 facility breakdown

Cluster	Cluster chemical total (pounds)[1]	Top 5 chemical total (pounds)[2]	% chemical releases in top 5 analysis[3]	Carcinogenic chemical release quantity (pounds)[4]	% carcinogenic chemical releases per cluster[5]
1	5,331,191	3,381,754	63%	30,126	1%
2	6,038,179	5,004,384	83%	1,307,629	26%
3	395,285	395,285	100%	36,933	9%
4	1,799,525	1,785,336	99%	28,085	2%
5	10,043	10,043	100%	3,861	38%
6	475,652	397,419	84%	15,946	4%
7	2,970,262	2,964,123	100%	1,199	0%
Total	17,020,137	13,938,344	--	1,423,778	--

[1]Sum of the total on-site releases from all 184 facilities within the study area

[2]Sum of total on-site releases for just the facilities included in the top five analysis

[3]Top five chemical releases total divided by cluster chemical releases total, then multiplied by 100%

[4]Sum of total on-site releases for just the carcinogens released from the top five facilities

[5]Carcinogenic chemical release quantity divided by top five chemical releases total, then multiplied by 100%

Quantity of chemical releases by cluster

The cluster that released the highest quantity of chemicals overall was Cluster 2 which released just over 6 million pounds of chemicals (Table 3). The five facilities used in our top five analysis accounted for 83% of the chemicals released in Cluster 2. The cluster that released the lowest quantity of chemicals was Cluster 5, which released just over 10,000 pounds of chemicals (Table 3). The facilities in the top five analysis accounted for 100% of the chemicals released in Cluster 5. This was due to Cluster 5 only having four facilities to include in our top five analysis. The cluster with the lowest percent of chemical releases in the top 5 analysis was Cluster 1 where the top five chemical total accounted for 63% of all chemicals released in the cluster. This showed us that by looking at the top five facilities we were, at a minimum, looking at least 63% of the total chemicals released in the cluster. Clusters 3 and 6 were the only two other clusters to release less than one million pounds of chemicals (Table 3). In every cluster, the releases from the top five facilities alone accounted for more than 60% of the cluster's overall chemical releases (Table 3). For that reason, we were able to only look at the top five facilities for analysis.

Quantity of carcinogenic chemical releases by cluster

The carcinogenic chemical releases in most clusters were low, typically never accounting for more than 10% of the chemicals released in our top five analysis. Cluster 7 had the lowest quantity of carcinogenic chemicals released across the top five facilities with 0% (Table 3). Cluster 7 is also the most rural of all the clusters (Figure 1). Cluster 5 had the highest percent of carcinogenic chemicals released. The facilities in Cluster 5 released just over 10,000 pounds of chemicals and almost 4,000 pounds of that were carcinogens (Table 3). Cluster 2 also had a high percentage of carcinogenic chemicals released. Cluster 2 released just over five million pounds of chemicals, and approximately one million pounds of those were carcinogens (Table 3).

Table 4. Top 5 Facility Scores per cluster, ranked from the highest (Facility 1) to the lowest (Facility 5).

Cluster	Facility 1	Facility 2	Facility 3	Facility 4	Facility 5
1	2.06×10^{10}	7.78×10^{9}	3.89×10^{9}	5.73×10^{8}	4.98×10^{8}
2	4.60×10^{10}	1.70×10^{10}	1.47×10^{10}	4.36×10^{9}	2.92×10^{9}
3	1.36×10^{9}	6.73×10^{8}	1.24×10^{7}	--	--
4	4.74×10^{9}	8.16×10^{8}	1.38×10^{8}	2.76×10^{7}	2.70×10^{6}
5	1.02×10^{8}	5.80×10^{7}	5.00×10^{4}	1.73×10^{4}	--
6	8.12×10^{9}	4.00×10^{9}	4.76×10^{8}	4.06×10^{8}	8.00×10^{7}
7	3.38×10^{7}	3.23×10^{7}	2.67×10^{7}	1.01×10^{7}	7.33×10^{6}

Facility Scores by cluster

The highest Facility Score in Cluster 1 was from Erie county, with a score of 2.06×10^{10} (Supplemental Table 2, Table 4). In this cluster, there were 38 chemicals released across the five facilities. Carcinogenic chemical releases accounted for less than 1% of all releases in this cluster (Table 3). Nickel and chromium, two known carcinogens, were each released from three of the five facilities, totaling 1,255 pounds each (Supplemental Table 2). The toxicity factors for both nickel and chromium are 9.3×10^5 and 4.3×10^7, respectively, and therefore these metals contribute heavily towards the Facility Score.

The highest Facility Score in Cluster 2 was 4.6×10^{10} (Table 4), and the facility with this score was found in Monroe County. This was the highest Facility Score of any of the facilities across our study area (Table 4, Figure 2). This cluster had 75 chemicals released across the top five facilities. Over 25% of the chemical releases from this cluster were considered carcinogenic (Table 3). Additionally, 99.7% of the total chemicals released, and 58 of the 75 chemicals released, originated from one facility, which is a business park (Supplemental Table 3). The highest Facility Score in Cluster 6 was 8.1×10^9 (Table 4). There were 29 chemicals released and eight of the chemicals released were carcinogenic (Supplemental Table 7).

The top facility scores from Clusters 3, 4, 5, and 7 were much lower than those in Clusters 1, 2, and 6 (Figure 2, Table 4). The closest facility scores to Cluster 1, 2, and 6 was in Cluster 4, where the highest facility score was 4.74×10^9 (Table 4), then Cluster 3, where the highest Facility Score was 1.36×10^9 (Table 4). All other top Facility Scores were at least an order of magnitude lower than the top Facility Scores in Clusters 1, 2, and 6 (Table 4).

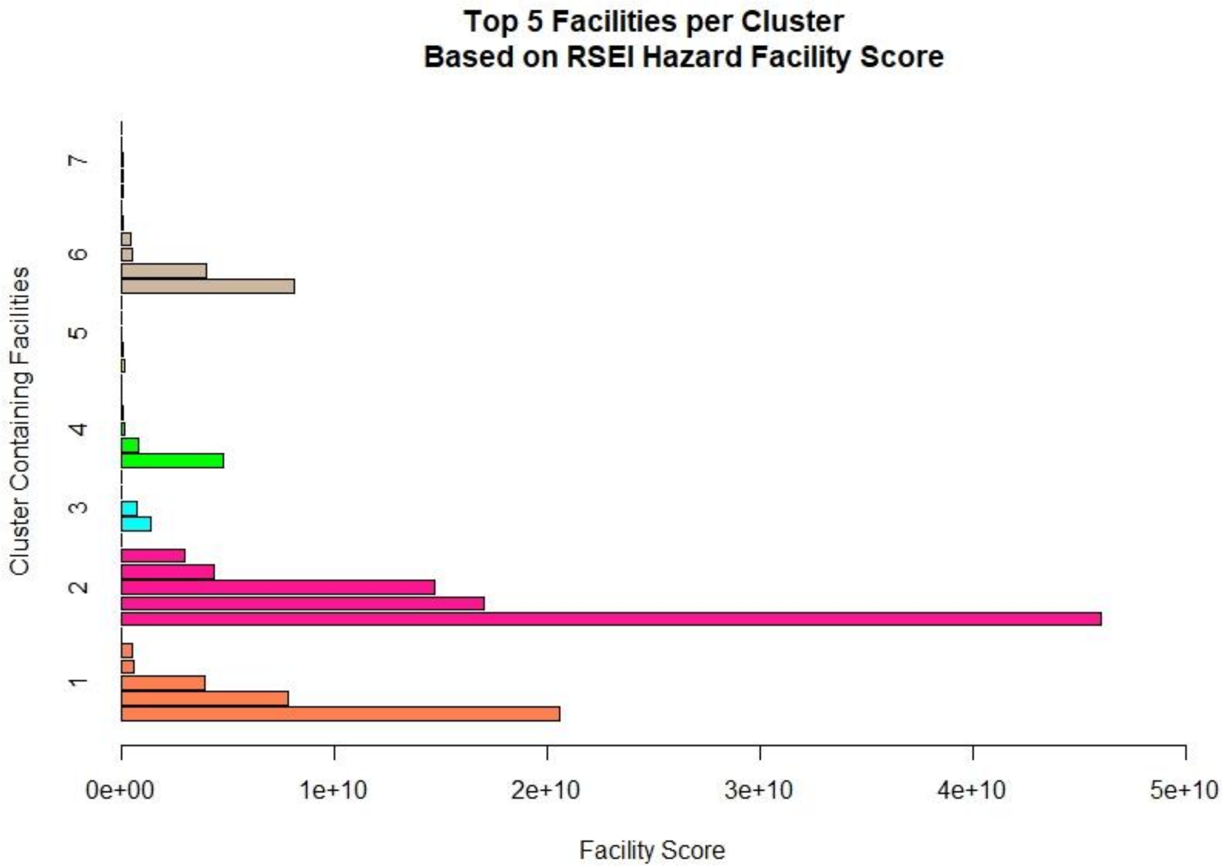


Figure 2. Top 5 Facilities per cluster based on RSEI Facility Score. This figure shows the Facility Scores of the top 5 facilities per cluster. The Facility Scores are presented on a logarithmic scale. The facilities with the highest Facility Scores are present in Clusters 1, 2, and 6. The highest Facility Scores in these three clusters are $2.06 \times 10^{10,}$ 4.60×10^{10}, and 8.12×10^{9}, respectively. For comparison, the next highest Facility Score from a different cluster comes from Cluster 4 at 4.74×10^{9}.

Facility Scores by county

The top five facilities chosen for each cluster appeared to be evenly spread out across Erie, Albany, and Onondaga Counties, but are heavily concentrated in Monroe County (Table 5). Those facilities residing in Erie, Monroe, and Albany Counties appear to be fairly clumped together in some areas whereas those in Onondaga County look to be fairly spread apart (Figure 3). Of the top five facilities per cluster, Clusters 1 and 5 had no facilities in Onondaga and Albany Counties, Cluster 2 had no facilities in Onondaga County, Cluster 3 had no facilities in Erie or Onondaga Counties, Cluster 4 had no facilities in Albany or Erie Counties, and Clusters 6 and 7 had no facilities in Monroe County (Table 5).

In Albany County, two of the facilities are in the northern portion of the county along the eastern border and three facilities are in the southeastern portion of the county. Two of these facilities are clumped together while the other one is further south (Figure 3). In Erie County, all the top five facilities are in the northern portion of the county. Six of the facilities are clumped together near the city of Buffalo, one facility is near the northeastern tip of the county, and one facility is in the middle of the county (Figure 3). The facilities in Onondaga County are all located near the middle of the county. There are three facilities to the west and two facilities to the east of Syracuse. The final facility is closer to the northwestern border of the county (Figure 3). Finally, in Monroe County, ten facilities are clumped around the Rochester area. There is one facility located on the northern border of the county and two facilities located near its eastern border (Figure 3).

Table 5. Top 5 Facility Score facilities broken down by county

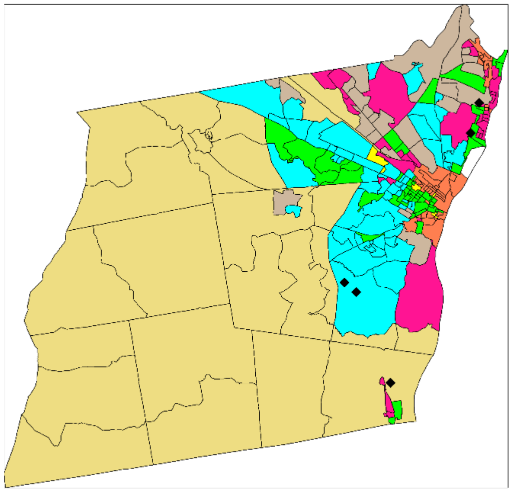
Cluster	Albany	Erie	Monroe	Onondaga
1	--	2	3	--
2	1	2	2	--
3	2	--	1	--
4	--	--	4	1
5	--	1	3	--
6	1	1	--	3
7	1	2	--	2
Total	5	8	13	6

Facility Scores by demographics

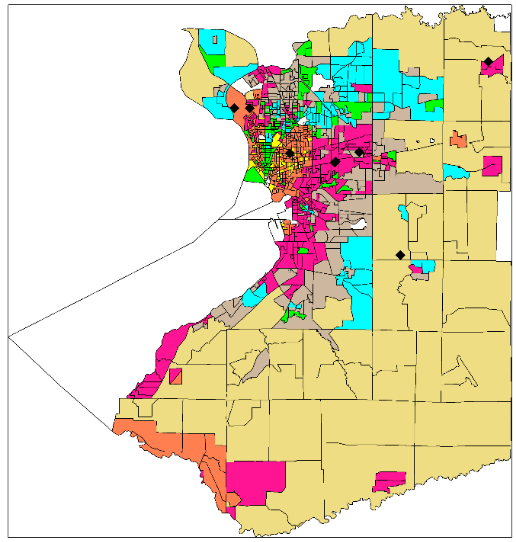
The clusters with the highest quantities of facilities releasing toxic compounds are Clusters 1, 2, and 6 (Figure 2). Clusters 1, 2, and 6 each present a unique set of sociodemographic factors, but the two factors of interest across the three of them would be the percent of the population working in non-managerial positions, and the percent of the population without a high school degree (Figure 1).

Cluster 1 had a lower than average percentage of high school graduates and owner-occupied housing. The cluster had a higher than average percent of single parent households, those not identifying as Non-Hispanic White, unemployment, those working in non-managerial positions, those below the poverty line, and percent vacant housing. The urban area in Cluster 1 was approximately 98% (Figure 1). Cluster 2 had a lower than average percentage of high school graduates, single parent households, those not identifying as Non-Hispanic White, unemployment, households below the poverty line, and percent vacant housing. This cluster had a higher than average percent of owner-occupied housing and those working in non-managerial positions. The area in Cluster 2 was 100% urban (Figure 1). Finally, Cluster 6 had a lower than average percentage of single parent households, those not identifying as Non-Hispanic White, unemployment, those working in non-managerial positions, those below the poverty line, and percent vacant housing. Cluster 6 had a higher than average percent of high school graduates and owner-occupied housing. The area in Cluster 6 was 100% urban (Figure 1).

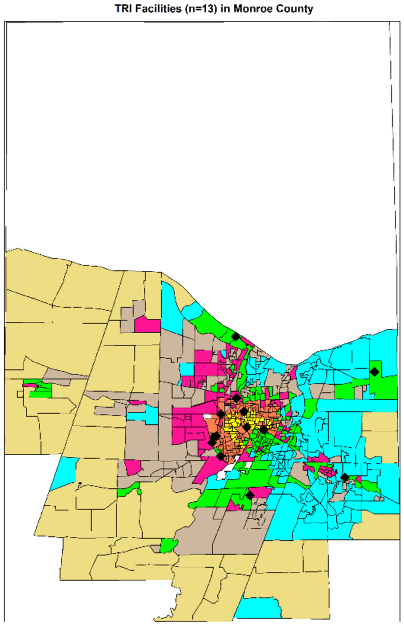
TRI Facilities (n=5) in Albany County



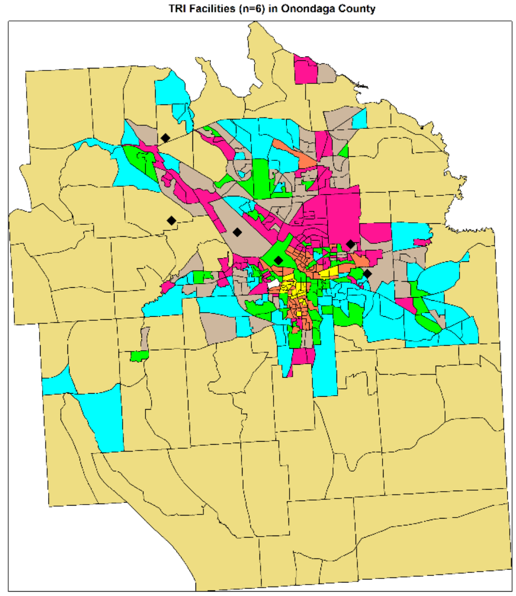
TRI Facilities (n=8) in Erie County



TRI Facilities (n=13) in Monroe County



TRI Facilities (n=6) in Onondaga County



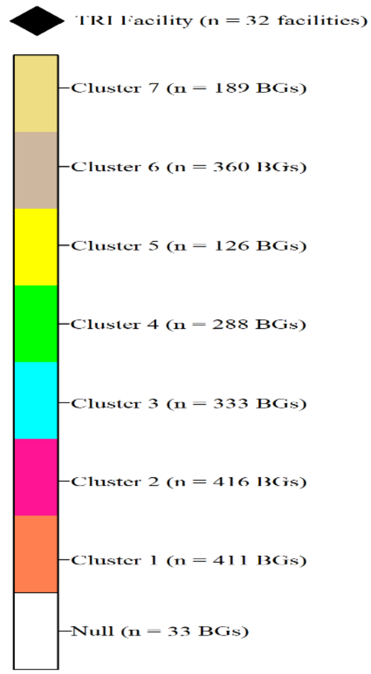


Figure 3. Location of the Top Five Toxic Release Inventory (TRI) facilities based on RSEI Facility Score. TRI facilities were geocoded within seven unique residential clusters comprised of 2,123 Census block groups in Albany, Erie, Monroe, and Onondaga Counties. 33 block groups having partial or no population were removed and are labeled as "Null".

Discussion

The main objective of this study was to determine if any particular demographic groups might be disproportionately exposed to higher quantities of toxic chemicals released from TRI facilities in four Upstate New York counties. Briefly, using hierarchical clustering, we created seven unique residential clusters based on nine socioeconomic status and land use variables. TRI facilities were then geocoded into these clusters. The quantity of chemical emissions, and RSEI Facility Scores, for each facility were obtained, and we closely examined the top five polluting facilities in each cluster. Then we looked to see if there were any trends in the socioeconomic status variables from the clusters that were potentially most impacted by the presence of these facilities. We found that Clusters 1 and 2 had the highest quantity of TRI facilities and chemical releases, and the facility with the highest RSEI Facility Score was located in Cluster 2. In looking solely at the RSEI data, the clusters with the highest Facility Scores were Clusters 1, 2, and 6. Interestingly, Cluster 6 had one of the lowest quantities of chemical releases across all seven clusters. Therefore, using the quantity of chemical releases as a metric for potential to harm human health may be misleading without having toxicity information. Lastly, the sociodemographic characteristics that stand out the most in the clusters with the highest quantity of chemicals being released, and highest RSEI Facility Scores were people working in non-managerial positions, and people without a high school degree.

In our work, we found that the presence of polluting facilities in an area isn't always indicative of the quantity of chemicals released from the polluting facilities. For example, Cluster 1 has almost eight times the number of facilities located within it as Cluster 7 (Table 2), yet the quantity of chemicals released from facilities in these clusters is roughly equivalent (Table 3). The outcome from one study demonstrated a disparity comparable to this. In this work, Sicotte & Swanson (2007) utilized Hazard Scores and looked at 291 TRI facilities in the Philadelphia area. They classified the facilities as low hazard (n = 144), medium hazard (n = 82), and high hazard (n = 65). They found that only 15% of all RSEI facilities, but 29% of high-hazard facilities, were in Philadelphia. Moreover, Montgomery County hosted 24% of all facilities, but just 14% of high hazard facilities. Further, a study conducted by Ash & Fetter (2002) pointed out that the presence of a polluting facility within a neighborhood has some validity as a sign of environmental quality, but its validity is limited when using it as a sign of actual exposure. The authors explain that the mass pollutants reported from the facility is a much closer proxy to environmental quality than just looking for the presence of a facility, thus validating our use of presence of facilities and quantity of chemical releases. This demonstrates that a higher quantity of facilities may not always mean more releases.

In our study area, we also found that a higher quantity of chemicals released does not necessarily indicative of higher Facility Scores either. For example, Clusters 5 and 7 had facilities with the lowest Facility Scores, suggesting their releases were some of the least toxic. This was in contract to Clusters 1, 2, and 6, which had the highest Facility Scores, suggesting their bulk releases were some of the most toxic of those being studied. Yet, if we were only to assess the quantity and not the toxicity, Clusters 1 and 7 were virtually equal in the quantity of chemicals they released across the top five facilities. This shows that not all exposure risk is considered equal and has been seen in other studies (Abel, 2008; Bouwes et al., 2001). In a study done by Abel (2008) in Missouri, it was seen that minority and low-income residents were disproportionately closer to industrial pollution sources. However, one-fifth of the region's air pollution over the last decade was concentrated amongst six facilities along the southwestern border of East St. Louis. Abel points out that data concerning pollution and health risk would be more advantageous to environmental managers than simply providing demographics about which groups are located closer to the facilities. In another study performed by Bouwes et al. (2001), the authors looked at the relationship between total air releases (in pounds), the hazard associated with those releases, and resulting risk to human health by state. In that work, Utah ranked 5th in the US for pounds of airborne releases, 19th from the hazard-based perspective, and 37th from the risk related perspective. Bouwes also goes on to state that the TRI data on quantity of emissions alone do not reveal the extent to which the public is at risk, and that the evaluation of risk must include the toxicity and dose of the chemical released. Therefore, integrating data from each cluster's Facility Scores, along with the number of polluting facilities and quantity of chemicals released, emphasize the importance of considering a chemical's toxicity along with the other metrics. By looking at the Facility Scores in an area, along with the quantity and identity of chemicals released, we are able to gain a much better understanding of who is potentially experiencing disproportionate exposure to more toxic chemicals.

For this study, we focused a lot of our attention on obtaining and comparing RSEI Facility Scores between our clusters. Most of the chemical analyses for this study involving Facility Scores were based upon the presence of carcinogens. Most chemicals are assigned a toxicity factor, but the toxicity factors of carcinogenic chemicals are usually orders of magnitude higher than the toxicity factors of non-carcinogenic chemicals, suggesting that a high quantity of carcinogens could increase the value of the Facility Score (United States Environmental Protection Agency, 2020b). Our Facility Scores were based on RSEI Modeled Hazard Scores, which are obtained by multiplying the quantity of a chemical released by the chemical's toxicity factor. As carcinogens typically have higher toxicity factors, they are going to contribute more to the overall Facility Score; however, this isn't always the case. For example, in Cluster 1 there were 38 total chemicals released, 12 of which were considered carcinogenic; however, the carcinogenic releases in that cluster amounted to less than a percent of the overall chemical releases for that cluster because these carcinogens were released in such low quantities.

The environmental justice literature has previously suggested that race and/or income are the two factors that would have the greatest influence over who would be disproportionately exposed to environmental pollutants (Chakraborty, 2009; Mohai et al., 2009; Mohai & Saha, 2007; Pastor et al., 2001; Perlin et al., 1995; Williams, 2008). One review on environmental justice by Mohai et al. (2009) brought up common scenario amongst environmental justice work: the chicken and the egg scenario. The scenario presents the question of whether the hazardous waste facilities came before the poor/minority populations or after. A study conducted by Pastor et al. (2001) found that the correspondence between polluting facilities and communities of color was based on a pattern of disparate siting of facilities in existing communities of color rather than on geographic shifts. However, this has not been shown in all environmental justice research. For example, a study done by Neumann et al. (1998) utilized a media-specific chronic toxicity index (CI) to rank TRI chemical releases. The researchers found that, although there was a disproportionate amount of TRI facilities located in minority neighborhoods, there was no correlation of race or ethnicity associated with the CI of a facility or the chemicals released. The results of our study appear to agree more with this work. Looking at just the Facility Scores we obtained, we can see that Clusters 1, 2, and 6 have the greatest quantity of toxic chemical releases. The only cluster of those three having a high percentage of minorities would be Cluster 1. Likewise, the clusters with high percentages of minorities (i.e., Clusters 4 and 5) both had low Facility Scores (Figure 2).

Previous studies have suggested that there might be a correlation between the types of laborers residing in neighborhoods and the location of polluting facilities (Brulle & Pellow, 2006; Williams, 2008). One example was a study done by Pastor et al. (2005). This research group found a positive association between the percentage of the local labor force in manufacturing and the most polluted Census tracts as compared to the least polluted Census tracts in the geographical area they were evaluating. We saw a similar trend of a high percentage of the population in the labor force in our study with Clusters 1, 2, and 6; however, the cluster with the highest percent of people in non-managerial positions in our study was Cluster 5, which had some of the lowest Facility Scores (Figure 2, Table 4). The reason Cluster 5 had such low Facility Scores has to do with the low amount of chemical releases from the facilities in that cluster. To begin, there was only nine chemicals released across the four facilities with a sum of just over 10,000 pounds of chemicals released, which was low compared to our other clusters (Table 3). Additionally, only one chemical released, trichloroethylene, was considered carcinogenic, and has a toxicity factor of 15,000, which is low for a carcinogen. Finally, this cluster was the most urban. This could indicate that the facilities located in that cluster are smaller and may release less chemicals overall. Most smaller facilities are also not obligated to report their releases to the EPA through the TRI program (United States Environmental Protection Agency, 2019a). Therefore, the low quantity of chemicals released, and the low toxicity scores lead to the low Facility Scores calculated in this cluster.

Education level has also been used as a variable in previous environmental justice studies, and lower levels of high school graduates has been cited previously in more polluted areas (Pastor et al., 2001; Sicotte & Swanson, 2007; Wilson et al., 2012). In the study conducted by Wilson et al. (2012), the authors used a linear regression model to evaluate the association between the number of TRI facilities in each census tract and their corresponding SES variables. For the percentage of the population with no high school diploma, they observed a positive and significant association with the number of TRI facilities. Additionally, in the study conducted by Sicotte & Swanson (2007), they looked at the demographics of the population living within one kilometer of either low-, medium-, or high-hazard facilities. The neighborhood demographics of those living near low- and medium-hazard facilities were demographically similar when compared to those not living near facilities. However, they noted that the proportion of college-educated residents dropped, and the proportion of high school dropouts increased amongst those living near high-hazard facilities. Our results appear to agree with these studies to an extent. In Clusters 1 and 2, we saw two of the lowest percentages of high school graduates. The lowest percentage of high school graduates was seen in Cluster 5, following the same trend as non-managerial positions.

There are a few reasons as to why the type of labor and high school education in an area might influence whether there are major polluting facilities around it. One reason, suggested by Wolverton (2009), is that when firms are looking to site a plant, they might think about the amount of skilled labor available in the area (Wolverton, 2009). In this work, the authors describe labor costs in an area as being related to the wage a plant pays its workers, the ease with which the plant can hire workers, and the qualifications of those workers. To evaluate these components, companies can look to several different factors, such as the average wage of a production worker in the area, and the percent of the population with at least a high school degree. Another important parameter they might consider is the percent of the population employed in manufacturing positions, which can be an indicator of the quantity of workers in the area matching the hiring needs of the plant.

In addition to the sociodemographic variables utilized in a study, the location and geographic scale of the study could also affect a study's outcome (Cutter et al., 1996; Perlin et al., 1995; Sicotte, 2010). In a study done by Cutter et al. (1996), different burdens of hazardous waste facilities at three different geographic scales were compared; the geographic scales studied included counties, census tracts, and census block groups. The group found there was some association between race and income and the presence of toxic facilities at the county level, but no associations at the census tract and census block group level. The author credited this discovery to there being no discernable difference between the racial composition of the census tracts, and wide intra-county and intra-zip code variations in risk and socioeconomic indicators. In a literature review performed by Sicotte (2010), the author stated that similar or identical methodologies in environmental justice studies may yield different patterns of inequality when applied to different metropolitan areas across the United States. One study in Phoenix, AZ found that the number of hazardous waste sites increased with the population percentages of African Americans and Latinos and decreased with household income and the percent population of whites (Bolin et al., 2002). Another study in New York found that percent minority was positively associated with the presence of hazards in Brooklyn, Queens, and the Bronx, but saw a negative association in Manhattan (Fricker & Hengartner, 2001). However, one group in South Carolina found that lower median income, and not the racial composition of block groups, predicted the presence of polluting facilities or hazardous waste sites (Cutter et al., 1996). Therefore, conclusions from environmental justice work must be read cautiously; in our instance, our results are specific to Upstate New York, at the block group level, and using the nine specific sociodemographic factors that we did.

The present study had several limitations. First, the data was taken from the 2000 US Census as opposed to the 2010 US Census because block group level data was not available for the chosen demographics in the 2010 US Census (Mirowsky et al., 2017; United States Census Bureau, 2019). However, data from the TRI program was also taken from the year 2000 to provide consistency across the study. Next, there are the limitations that come with the databases we chose to use. With the TRI program, there is a minimum reporting limit, meaning that smaller facilities are exempt from reporting their releases. This might have influenced our findings for Cluster 5. Also, the data from this program relies on self-reported information (Dolinoy & Miranda, 2004; United States Environmental Protection Agency, 2019a; Wilson et al., 2012). The RSEI program takes its data from the TRI program, so any limitation related to TRI facilities impacts the values obtained from the RSEI program. RSEI also does not provide scores for all TRI chemicals because information required for modeling, such as toxicity data, is not available for every chemical (United States Environmental Protection Agency, 2017a). However, Toffel and Marshall (2004) conducted a study on 13 different chemical weighting systems and stated that the RSEI model was unique in its inclusion of site-specific exposure and population characteristics, such as age and gender, along with multiple other benefits to using this model. Additionally, at the time of Toffel and Marshall's publication, the RSEI model conveyed the most information pertaining to TRI substances of the 13 models analyzed. Finally, our study did not consider the transport of chemicals across block groups and only considered the sociodemographic factors of the cluster the facility lies in. This was done to ensure we were looking at each cluster evenly, and only examining the top five facilities in that cluster.

There are also several strengths of this study. First, this study utilized a novel clustering technique to include all variables deemed important rather than reducing our indicators using statistical techniques. The technique has only been demonstrated in a handful of other studies (Humphreys & Carr-Hill, 1991; Mirowsky et al., 2017; Weaver et al., 2019). Next, block groups were utilized for the creation of the clusters. Block groups are the smallest denomination to report social characteristics in the US Census (Lemery, 2019). By looking at our data on a smaller scale, we can more accurately cluster residential data based upon similarities in population demographics. Another strength to our work was that in our literature search, we found very few studies similar to our work, monitoring TRI facilities and determining potential disproportionate exposure, that used Upstate New York as the study location (Hill et al., 2018). By conducting this research in an area not so heavily studied, we are able to provide more information about potential environmental pollutants and their levels of exposure in other areas. This could be important information, since Buffalo, Albany, Rochester, and Syracuse, NY have all been credited as the poorest cities within their respective counties. One group used the most recent Census data to find the median household income of all towns, villages, and cities across New York State, and divided the results by county. Their work showed that in our study area, we were looking at the areas that could use the most help (Axelson, 2019). Finally, the studying of both the quantity of chemicals released and the toxicity of chemicals released has only been seen in a handful of studies (Lim et al., 2010).

Conclusions

In conclusion, we utilized a novel clustering technique to establish seven unique residential clusters in Albany, Erie, Monroe, and Onondaga Counties. Within these counties, we geocoded all TRI facilities with an EPA-provided RSEI Facility Score to determine if any trend was present in both the quantity of chemicals released, as well as the toxicity of the releases and the sociodemographic groups living near those facilities. The top five Facility Scores were examined more closely to look specifically at the chemicals being released. The demographics that might be disproportionately exposed to more severe chemicals were the population in non-managerial positions, and the population without a high school diploma. Clusters 1, 2, and 6, which had the highest and most consistent Facility Scores, were the clusters that had three of the highest percentages of workers in non-managerial positions. Additionally, Clusters 1 and 2 had two of the lowest percentages of high school graduates.

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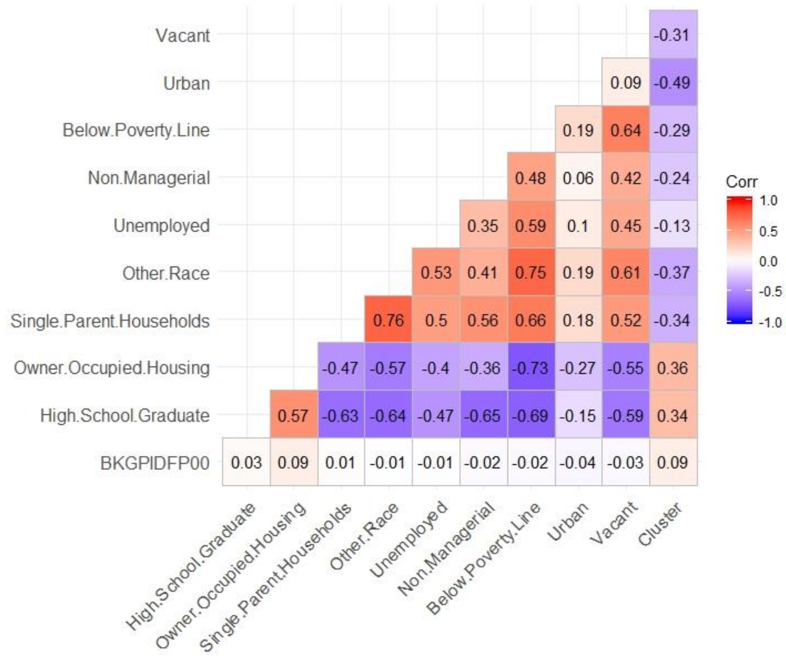
Supplemental Information



Supplemental Figure 1. Pearson correlation coefficients between each of the nine variables.

Supplemental Table 1. County Size

County	Major City	Total land area (square miles)	Major city land area (square miles)
Albany	Albany	522.80	21.39
Erie	Buffalo	1,042.69	40.38
Monroe	Rochester	657.21	35.78
Onondaga	Syracuse	778.39	25.04

Source: (United States Census Bureau, 2019)

It is important to note that the general formula for determining a RSEI Modeled Hazard Score is multiplying the pounds of a chemical released by the chemical's toxicity weight. For example, in Supplemental Table 2, for Facility 1 the RSEI Modeled Hazard Score for Manganese compounds for air releases would be 1.20×10^4 multiplied by 425 which would be 5.1×10^6. Doing this for all chemicals released form a facility, then adding those scores together should produce a Facility Score. However, this method is very flexible, and countless variations can be produced (United States Environmental Protection Agency, 2019d) so any Facility Scores calculated from Supplemental Tables 2 through 8 may not yield the exact EPA calculated Facility Score.

Supplemental Table 2. Cluster 1 summary of top 5 chemicals* released

Facility	County	Chemical	Air toxicity weight	Water toxicity weight	Total air releases (pounds)	Total water releases (pounds)
1	Erie	Manganese Compounds	1.20E+04	7.10E+00	425	36000
		Zinc Compounds	1.00E+02	3.30E+00	275	17000
		Nickel Compounds	9.30E+05	9.10E+01	445	20000
		Arsenic Compounds	1.50E+07	1.50E+06	635	1
		Polycyclic Aromatic Compounds*	3.90E+05	--	1.7	0
		Mercury Compounds	1.20E+04	--	274	0
		Hydrogen Fluoride	2.50E+02	--	190000	0
		Cobalt Compounds*	1.70E+07	1.70E+07	165	14000
		Chromium Compounds (Except Chromite Ore Mined in The Transvaal Region)	4.30E+07	5.00E+05	425	26000
		Dioxin and Dioxin-Like Compounds	1.40E+09	--	0.29	0
		Hydrochloric Acid (1995 and After Acid Aerosols" Only)"	1.80E+02	--	2400000	0
		Benzo(G,H,I)Perylene*	2.00E+04	--	0.04	0
		Barium Compounds	7.00E+03	5.00E+00	1005	84000
		Sulfuric Acid (1994 and After Acid Aerosols" Only)"	3.50E+03	--	500000	0
		Vanadium Compounds	1.40E+02	1.40E+02	515	60
2	Monroe	Chromium*	4.30E+07	--	500	0
		Manganese	1.20E+04	--	500	0
		Nickel*	9.30E+05	--	500	0
3	Monroe	Chromium*	4.30E+07	--	250	0
		Nickel*	9.30E+05	--	250	0
4	Erie	Chromium*	4.30E+07	5.00E+05	255	250

		Manganese	1.20E+04	7.10E+00	255	250
		Nickel*	9.30E+05	9.10E+01	255	250
5	Monroe	Zinc Compounds	1.00E+02	--	78	0
		N,N-Dimethylformamide*	1.20E+02	--	1	0
		Chloroform*	8.20E+04	--	2953	0
		Carbon Tetrachloride*	2.10E+04	--	10495	0
		Certain Glycol Ethers	1.80E+02	--	3	0
		Pyridine	1.00E+03	--	21321	0
		Methanol	1.80E-01	--	11455	0
		N-Hexane	5.00E+00	--	38718	0
		Acetonitrile	5.80E+01	--	344	0
		Perchloromethyl Mercaptan	N/A	--	90	0
		Sodium Azide	2.50E+02	--	0	0
		Ammonia	7.00E+00	--	905	0
		3-Iodo-2-Propynyl Butylcarbamate	1.40E+01	--	0	0
		Ethylene Glycol	8.80E+00	--	27	0
		Chlorine	2.30E+04	--	622	0

* Classified as a carcinogenic chemical

Supplemental Table 3. Cluster 2 summary of top 5 chemicals* released

Facility	County	Chemical	Air toxicity weight	Water toxicity weight	Total air releases (pounds)	Total water releases (pounds)
1	Monroe	Silver Compounds	2.00E+02	2.00E+02	2605	6053
		Cyclohexane	5.80E-01	--	22100	0
		Sodium Nitrite	1.00E+01	--	0	0
		Dibutyl Phthalate	1.00E+01	1.00E+01	41	47
		Vinylidene Chloride	1.80E+01	--	182	0
		Methyl Isobutyl Ketone	1.20E+00	1.30E+01	7010	1700
		Sulfuric Acid (1994 and After Acid Aerosols" Only)"	3.50E+03	--	570003	0
		Pyridine	1.00E+03	1.00E+03	503	200
		Formaldehyde*	4.60E+04	5.00E+00	2200	1
		Styrene*	3.50E+00	5.00E+00	291	140
		Barium Compounds	7.00E+03	5.00E+00	25000	6000

		Chlorine	2.30E+04	--	55000	0
		Methyl Methacrylate	5.00E+00	7.10E-01	113	5
		Hydrogen Fluoride	2.50E+02	--	160000	0
		Ethylene Glycol	8.80E+00	5.00E-01	4700	9200
		Formic Acid	--	--	0	0
		Nitrate Compounds	6.30E-01	6.30E-01	76	570000
		Zinc Compounds	1.00E+02	3.30E+00	6100	12160
		Antimony Compounds	1.80E+04	2.50E+03	1600	4900
		Hydrochloric Acid (1995 and After Acid Aerosols" Only)"	1.80E+02	--	1400100	0
		Chloromethane	6.40E+02	--	450	0
		Xylene (Mixed Isomers)	3.50E+01	5.00E+00	16920	140
		Chlorophenols*	1.20E+05	1.20E+05	5	16
		Methanol	1.80E-01	5.00E-01	481000	25000
		Benzo(G,H,I)Perylene*	2.00E+04	--	0.029	0
		Toluene	7.00E-01	1.30E+01	61300	540
		2-Methoxyethanol	1.80E+02	--	968	0
		Diethanolamine	1.20E+03	7.10E+02	3	3
		1,2-Dichloropropane	8.80E+02	1.10E+01	13300	81
		Aniline	5.70E+03	5.70E+03	322	6
		Methyl Acrylate	1.80E+02	--	80	0
		Nitric Acid	2.70E+02	--	1808	0
		N-Methyl-2-Pyrrolidone	N/A	N/A	60000	740
		Ammonia	7.00E+00	7.00E+00	7700	23039
		Dimethylamine	--	--	0	0
		Cresol (Mixed Isomers)	5.80E+00	2.00E+01	281	210
		Hydroquinone	2.50E+01	2.50E+01	510	120
		Methyl Ethyl Ketone	7.00E-01	1.70E+00	24600	5200
		Mercury Compounds	1.20E+04	1.00E+04	25	4
		Acetaldehyde*	7.90E+03	--	18100	0
		N,N-Dimethylaniline	5.00E+02	5.00E+02	88	670
		1,4-Dioxane*	1.80E+04	1.00E+05	2940	5000
		Acetonitrile	5.80E+01	5.80E+01	10300	2900
		M-Cresol	--	--	0	0
		Certain Glycol Ethers	1.80E+02	1.80E+02	14400	4000
		N,N-Dimethylformamide*	1.20E+02	1.00E+01	4002	95
		Catechol	--	9.00E+03	0	9
		N-Butyl Alcohol	1.00E+01	1.00E+01	23420	140
		Propylene Oxide*	1.30E+04	--	1522	0
		Phenol	1.80E+01	3.30E+00	403	49

		Butyl Acrylate	3.50E+03	2.00E+00	119	19
		Acrylamide*	--	5.00E+05	0	3
		Triethylamine	5.00E+02	--	2520	0
		Dichloromethane*	3.60E+01	2.00E+03	1267000	2700
		Polycyclic Aromatic Compounds*	3.90E+05	1.80E+05	0.881	1.7
		Ozone	1.90E+01	--	33040	0
		Dioxin and Dioxin-Like Compounds	1.40E+09	1.40E+09	2.31	2.68
		Chromium Compounds (Except Chromite Ore Mined in The Transvaal Region)	4.30E+07	5.00E+05	2800	936
2	Albany	Manganese	1.20E+04	--	109	0
		Chromium*	4.30E+07	--	1132	0
		Nickel*	9.30E+05	--	479	0
		Nitric Acid	2.70E+02	--	1053	0
		Hydrogen Fluoride	2.50E+02	--	2935	0
3	Erie	Methyl Ethyl Ketone	7.00E-01	--	6490	0
		Chromium*	4.30E+07	--	750	0
		Nickel*	9.30E+05	--	250	0
4	Erie	Nickel*	9.30E+05	--	750	0
		Chromium*	4.30E+07	--	250	0
		Manganese	1.20E+04	--	250	0
5	Monroe	Chromium Compounds (Except Chromite Ore Mined in The Transvaal Region)	4.30E+07	--	200	0
		Nitrate Compounds	6.30E-01	--	26	0
		Manganese	1.20E+04	--	0	0
		Zinc Compounds	1.00E+02	--	10	0
		Copper	1.50E+03	--	0	0
		Nickel*	9.30E+05	--	0	0

* Classified as a carcinogenic chemical

Supplemental Table 4. Cluster 3 summary of top 5 chemicals* released

Facility	County	Chemical	Air toxicity weight	Water toxicity weight	Total air releases (pounds)	Total water releases (pounds)
1	Albany	Ammonia	7.00E+00	--	140092	0

		Chromium Compounds (Except Chromite Ore Mined in The Transvaal Region)	4.30E+07	--	16	0
		Formaldehyde*	4.60E+04	--	27522	0
2	Albany	Chromium Compounds (Except Chromite Ore Mined in The Transvaal Region)	4.30E+07	5.00E+05	43	11
		Antimony Compounds	1.80E+04	2.50E+03	2	11
		Ethylbenzene	8.90E+02	1.10E+03	1780	11
		Zinc Compounds	1.00E+02	3.30E+00	70	540
		Nickel Compounds	9.30E+05	9.10E+01	40	73
		Styrene*	3.50E+00	5.00E+00	9400	11
		Cresol (Mixed Isomers)	5.80E+00	2.00E+01	4700	100
		2,4-Dimethylphenol	5.00E+01	--	173	0
		Xylene (Mixed Isomers)	3.50E+01	5.00E+00	4760	43
		Toluene	7.00E-01	1.30E+01	115000	2
		Methanol	1.80E-01	5.00E-01	57000	90
		Copper Compounds	1.50E+03	1.50E+03	1500	360
		Nitrate Compounds	--	6.30E-01	0	29000
		Phenol	1.80E+01	--	2400	0
3	Monroe	Nickel Compounds	9.30E+05	9.10E+01	10	5
		Manganese Compounds	1.20E+04	7.10E+00	255	5
		Zinc Compounds	1.00E+02	3.30E+00	255	5

*Classified as a carcinogenic chemical

Supplemental Table 5. Cluster 4 summary of top 5 chemicals* released

Facility	County	Chemical	Air toxicity weight	Water toxicity weight	Total air releases (pounds)	Total water releases (pounds)
1	Onondaga	Chromium Compounds (Except Chromite Ore Mined in The Transvaal Region)	4.30E+07	--	255	0
		Nickel Compounds	9.30E+05	--	500	0
		Zinc Compounds	1.00E+02	--	255	0
		Copper Compounds	1.50E+03	--	500	0
		Ammonia	7.00E+00	--	1500	0
		Nitrate Compounds	6.30E-01	--	500	0
		Nitric Acid	2.70E+02	--	1000	0
2	Monroe	Mercury Compounds	1.20E+04	--	65	0
		Benzo(G,H,I)Perylene*	--	--	0	0
		Barium Compounds	7.00E+03	5.00E+00	445	42
		Hydrogen Fluoride	2.50E+02	--	68000	0
		Dioxin And Dioxin-Like Compounds	1.40E+09	--	0.19	0
		Sulfuric Acid (1994 and After Acid Aerosols" Only)"	3.50E+03	--	150000	0
		Polycyclic Aromatic Compounds*	3.90E+05	--	0.57	0
		Hydrochloric Acid (1995 and After Acid Aerosols" Only)"	1.80E+02	--	1500000	0
3	Monroe	Copper	1.50E+03	--	10	0
		Nickel*	9.30E+05	--	32	0
		Chromium*	4.30E+07	--	14	0
4	Monroe	Xylene (Mixed Isomers)	3.50E+01	--	653	0
		Polycyclic Aromatic Compounds*	3.90E+05	--	0.11	0
		Ethylbenzene	8.90E+02	--	140	0
		Benzene*	2.80E+04	--	978	0
		Toluene	7.00E-01	--	1471	0
		N-Hexane	5.00E+00	--	1714	0
		Benzo(G,H,I)Perylene*	--	--	0	0
5	Monroe	Methyl Ethyl Ketone	7.00E-01	--	14669	0
		Methyl Isobutyl Ketone	1.20E+00	--	5492	0
		Dichloromethane*	3.60E+01	--	27060	0

		Certain Glycol Ethers	1.80E+02	--	9514	0
		Toluene	7.00E-01	--	526	0

*Classified as a carcinogenic chemical

Supplemental Table 6. Cluster 5 summary of top 5 chemicals* released

Facility	County	Chemical	Air toxicity weight	Water toxicity weight	Total air releases (pounds)	Total water releases (pounds)
1	Erie	Nickel Compounds	9.30E+05	--	110	0
2	Monroe	Ammonia	7.00E+00	--	5532	0
		Trichloroethylene*	1.50E+04	--	3861	0
3	Monroe	Zinc Compounds	1.00E+02	--	500	0
4	Monroe	Methanol	1.80E-01	--	10	0
		Naphthalene	--	--	0	0
		Diethanolamine	1.20E+03	--	10	0
		Triethylamine	5.00E+02	--	10	0
		2,4-Db	3.30E+01	--	10	0

*Classified as a carcinogenic chemical

Supplemental Table 7. Cluster 6 summary of top 5 chemicals* released

Facility	County	Chemical	Air toxicity weight	Water toxicity weight	Total air releases (pounds)	Total water releases (pounds)
1	Onondaga	Nitric Acid	2.70E+02	--	694	0
		Chromium*	4.30E+07	5.00E+05	3074	169
		Nitrate Compounds	--	6.30E-01	0	20015
		Manganese	1.20E+04	7.10E+00	2064	82
		Nickel*	9.30E+05	9.10E+01	1040	267
		Cobalt*	1.70E+07	1.70E+07	186	43
		Copper	1.50E+03	1.50E+03	232	28
2	Onondaga	Certain Glycol Ethers	1.80E+02	--	10500	0
		Nickel*	9.30E+05	9.10E+01	255	60
		Copper	1.50E+03	1.50E+03	255	70
		Diisocyanates	3.50E+05	--	45	0
		Chromium*	4.30E+07	5.00E+05	255	5

		Polycyclic Aromatic Compounds*	--	--	0	0
		Chlorodifluoromethane	7.00E-02	--	28400	0
		Manganese	1.20E+04	7.10E+00	500	170
3	Albany	Formaldehyde*	4.60E+04	--	10350	0
		Manganese Compounds	--	--	0	0
		Phenol	1.80E+01	--	11200	0
4	Onondaga	Nickel Compounds	9.30E+05	--	255	0
		Chromium Compounds (Except Chromite Ore Mined in The Transvaal Region)	4.30E+07	--	10	0
		Nitric Acid	2.70E+02	--	2703	0
		Cyanide Compounds	4.40E+03	--	10	0
		Copper Compounds	1.50E+03	--	10	0
		Nitrate Compounds	--	--	0	0
5	Erie	Polycyclic Aromatic Compounds*	3.90E+05	--	202	0
		Copper	--	--	0	0
		Xylene (Mixed Isomers)	3.50E+01	--	27907	0
		Zinc Compounds	--	--	0	0
		Toluene	7.00E-01	--	276313	0

* Classified as a carcinogenic chemical

Supplemental Table 8. Cluster 7 summary of top 5 chemicals* released

Facility	County	Chemical	Air toxicity weight	Water toxicity weight	Total air releases (pounds)	Total water releases (pounds)
1	Onondaga	Benzene*	2.80E+04	--	1196	0
		Toluene	7.00E-01	1.30E+01	1940	5
		Polycyclic Aromatic Compounds*	3.90E+05	--	0.13	0
		Xylene (Mixed Isomers)	3.50E+01	--	985	0
		N-Hexane	5.00E+00	--	2034	0
		Ethylbenzene	8.90E+02	--	221	0
		Benzo(G,H,I)Perylene*	--	--	0	0
2	Erie	Chromium*	4.30E+07		3	0

3	Onondaga	Polycyclic Aromatic Compounds*	--	--	0	0
		Nitrate Compounds	--	6.30E-01	0	2797689
		Benzo(G,H,I)Perylene*	--	--	0	0
		Sulfuric Acid (1994 and After Acid Aerosols" Only)"	3.50E+03	--	7098	0
		Ammonia	7.00E+00	7.00E+00	17106	210
4	Erie	Diisocyanates	3.50E+05	--	2	0
		Certain Glycol Ethers	1.80E+02	--	46495	0
		Urethane*	--	--	0	0
		Barium Compounds	7.00E+03	--	144	0
5	Albany	Dioxin and Dioxin-Like Compounds	1.40E+09	--	1.89	0
		Hydrochloric Acid (1995 and After Acid Aerosols" Only)"	1.80E+02	--	36657	0
		Mercury	1.20E+05	--	38.4	0
		Methanol	1.80E-01	--	52272	0

* Classified as a carcinogenic chemical

CHAPTER 4: CONCLUSIONS

Conclusions regarding the presence of Toxic Release Inventory (TRI) facilities (Chapter 2)

In this research, we used a hierarchical clustering method to aggregate 2,123 census block groups across Albany, Erie, Monroe, and Onondaga Counties into seven unique residential clusters based upon 9 US Census demographic variables. These variables included the percent of the population that graduated from high school, the percent of the population in owner occupied housing, the percent of the population with income below the poverty line, the percent of the population not identifying as Non-Hispanic White, the percent of the population unemployed, the percent of the population working in non-managerial positions, the percent of the population with a single parent household, the percent of vacant housing in an area, and the percent of the area in the cluster that was urban. Using TRIExplorer, we were able to obtain the location of all the Toxic Release Inventory (TRI) facilities in our study area and geocode them within our seven residential clusters. Geocoding these facilities within our clusters allowed us to determine if there was a relationship between any residential cluster characteristics and the presence and location of these TRI facilities.

Our hypothesis for this study stated that we assumed that minorities and low-income households were going to be the two groups that were disproportionately exposed to these polluting facilities and higher quantities of chemical releases. Based on our work, there was no clear relationship seen between race or income levels and the presence of TRI facilities. This could be seen by looking at the presence of the TRI facilities within the residential clusters we formed. While Cluster 1 did have a high percentage of minorities, Cluster 2 did not. Additionally, the only cluster other than Cluster 1 that had a higher than average percentage of minorities was Cluster 5, which only had 8 facilities. In terms of low-income households, Cluster 1, again, had a higher percentage of people living below the poverty line, but Cluster 2 did not.

Another conclusion we drew from this work was that the characteristic that seemed to be most influential in the location of these facilities was the percent of the population working in non-managerial positions. Looking at Clusters 1 and 2, which were the clusters with the highest number of facilities, we see a disproportionately high percentage of the population employed in non-managerial positions. This was the only variable that was either consistently high or consistently low between Clusters 1 and 2. Additionally, the population working in non-managerial positions also appeared to be exposed to higher quantities of chemical releases. The facilities within Cluster 1 released 5.3 million pounds of chemicals and the facilities within Cluster 2 released just over 6 million pounds of chemicals. Together, the facilities in these two clusters accounted for 67% of the total on-site releases in our study area. One explanation for why we may be seeing facilities located near the working-class population would be because a higher percentage of people working in non-managerial positions in an area could provide a proximity to work for the employee, and skilled labor for the employer.

Conclusions regarding Risk-Screening Environmental Indicators (RSEI) Facility Scores (Chapter 3)

In this work, we used a novel clustering technique to aggregate census block groups into seven unique residential clusters across Albany, Erie, Monroe, and Onondaga Counties based upon nine US Census variables. Using TRIExplorer, we were able to obtain information on all the Toxic Release Inventory (TRI) facilities within our four-county study area and geocode them within our seven residential clusters. Using the Risk-Screening Environmental Indicators (RSEI) model, we were able to obtain Facility Scores for all 184 TRI facilities in our study area. From those scores, we were able to determine the top five facilities per cluster with the highest Facility Scores. The top five facilities were examined more closely to determine which chemicals were being released, and in what quantity the chemicals were being released. The clusters that had the highest Facility Scores were located in Clusters 1, 2, and 6. Clusters 1 and 2 had the highest quantities of chemicals released across all seven clusters and had the highest Facility Scores across all seven clusters. Cluster 6 had one of the lowest quantities of chemicals released across our study area, but still had some of the highest Facility Scores.

Based upon our previous work, the hypothesis for this study was that those working in non-managerial positions was going to be the demographic that might be disproportionately exposed to more toxic chemicals, based on RSEI Facility Scores. Based upon RSEI Facility Scores, we determined that the three clusters that had the highest potential to be exposed to more toxic chemicals were Clusters 1, 2, and 6. These three clusters had three of the highest Facility Scores in our study area. The highest Facility Score in Cluster 1 was 2.06×10^{10}, the highest Facility Score in Cluster 2 was 4.60×10^{10}, and the highest Facility Score in Cluster 6 was 8.12×10^{9}. Looking at the demographics of Clusters 1, 2, and 6, we can see that those clusters have three of the highest percentages of workers in non-managerial positions. In Cluster 1, 79% of the population worked in non-managerial positions, in Cluster 2, 75% of the population worked in non-managerial positions, and in Cluster 6, 64% of the population worked in non-managerial positions. However, that doesn’t appear to be the only demographic at risk for more severe exposure. Clusters 1 and 2 also had two of the lowest percentages of high school graduates, with 69% in Cluster 1 and 80% in Cluster 2. This led us to believe this demographic may also be disproportionately exposed to more severe chemicals.

Future work

Our work in the environmental justice field is far from over; many manipulations and changes could be made to our studies to lead us to new conclusions and a better understanding of our study area. First, we could look at the demographics within a certain radius around the TRI facilities in our study area, as opposed to unit-hazard coincidence, to see if those in non-managerial positions are still the most affected by the presence of these facilities, or if another variable is more exposed. Next, we could potentially investigate the demographics surrounding these facilities at the time they were sited, as opposed to in one study year, and determine if the populations in the area or the facilities were located first. This could allow us to contribute to the chicken or the egg scenario. Next, this work could be expanded to different study locations to determine if our findings are unique to our study area in Upstate New York, or if there are a more general trend. Also, our research could be expanded to included population and health data. As stated, the Facility Scores we utilized were based upon RSEI Modeled Hazard Scores. We could redo this study using RSEI Scores to see if the same results are found. Also, we could incorporate health data into our clusters, and see if any potential trends arise between any demographic variables and the prevalence of certain diseases.

Curriculum Vitae

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EDUCATION

State University of New York College of Environmental Science and Forestry	Syracuse, NY
Master of Science, Environmental Chemistry	Anticipated May 2020 GPA: 3.359
University of New Haven	West Haven, CT
Bachelor of Science, Forensic Science **Bachelor of Science, Chemistry**	May 2018 GPA: 3.49

Dean's List (Fall 2014 – Fall 2016), Alpha Lambda Delta Honor Society, Honors Program, Distinguished Scholar Award

RESEARCH

State University of New York College of Environmental Science and Forestry	Syracuse, NY
Measuring Residential Socioeconomic Factors Associated with Pollutant Releases using EPA's Toxic Release Inventory	November 2018 - Present
Assessing the relationship between neighborhood socioeconomic status and toxic chemical releases in Upstate New York	December 2019 - Present
University of New Haven Forensic Science Department	West Haven, CT
The Analysis of Pre-Workout Supplements Using Portable and Non-Portable FTIR	May 2017 – May 2018

AWARDS AND HONORS

State University of New York College of Environmental Science and Forestry	Syracuse, NY
Exceptional Service as a Graduate Teaching Assistant	May 2019

Graduate Student Summer Fellowship May 2019

- Conrad Schuerch Chemistry Graduate Scholarship

RELEVANT LAB EXPERIENCE

Demonstrate proficiency with the following instruments: Shimadzu UV-2600 UV-VIS Spectrophotometer, Shimadzu RF-535 Fluorescence HPLC Monitor, Magritek Spinsolve NMR, Perkin Elmer 3110 Atomic Absorption Spectrometer, Shimadzu EDX-720 Energy Dispersive X-Ray Spectrophotometer

Demonstrate proficiency in RStudio Programming Software

State University of New York College of Environmental Science and

Forestry Forest Chemistry Department Syracuse, NY

Graduate Student Teaching Assistant – Hybrid Laboratory Teaching Assistant August 2019 – December 2019

- Teach a one-hour recitation section once a week with up to 25 students present
- Prepare supplied lecture material and questions to engage students and help them develop in areas they may be struggling
- Grade up to 25 students' weekly quizzes and report in Blackboard
- Complete all responsibilities outlined under *Graduate Student Teaching Assistant - Laboratory Teaching Assistant*

Graduate Student Teaching Assistant – Laboratory Teaching Assistant August 2018 – May 2019
January 2020 – May 2020

- Engage with up to 60 students in a laboratory setting and perform General Chemistry experiments
- Practice working within standard lab safety protocols and ensure quality control is maintained where possible
- Perform one hour of office hours a week to aid students struggling with General Chemistry practices
- Restock and prepare laboratory setting from provided material for labs occurring after mine
- Grade up to 25 students' worksheets and lab reports pertaining to the previous week's laboratory experiment

University of New Haven Chemistry Department West Haven, CT

Laboratory Assistant August 2017 – May 2018

- Practiced working within standard lab safety protocols, and ensured Quality Control is maintained whenever necessary

- Aided 16 students struggling with the principles of Quantitative Analysis and General Chemistry on a weekly basis

General Chemistry Recitation Lecture Assistant January 2017 – May 2018

- Aided more than 30 students struggling with the principle foundations of General Chemistry on a weekly basis
- Taught and provided resources to allow students to understand their material

Summer Worker May 2017 – August 2017

- Organized and stocked over 800 organic and inorganic chemicals, and created entries for all chemicals on MSDSOnline
- Prepared materials for more than 100 students to partake in a variety of chemistry-based labs for the upcoming fall semester
- Demonstrated proficiency in the preparation of labs by organizing Lab Assistant Preparation Sheets

NON-LABORATORY JOB EXPERIENCE

Bangor Parks and Recreation Bangor, ME

Summer Camp Lead June 2018 – August 2018

- Lead a staff of six people along with a Camp Supervisor
- Aided in the care of up to 70 campers falling in the age group of first grade to third grade
- Developed a weekly educational and creative outline for camp activities over a 10-week timeframe

University of New Haven Office of Residential Life West Haven, CT

Senior Resident Assistant August 2017 – May 2018

- Participated in a weekly duty rotation schedule
- Assisted the Resident Director on Duty in all residential life issues
- Utilized critical thinking, leadership, teamwork, global awareness, communication, and resilience skills on a day to day basis
- Participated in a Competency Learning Experience to access progress in the previous six competencies
- Analyzed attendance data for programs put on through all eleven areas within the residential life scope
- Developed an automated program to designate use of attendance readers for all eleven areas within the residential life scope
- Completed all responsibilities outlined in *Forensic Science Living Learning Community Resident Assistant*

Forensic Science Living Learning Community

Resident Assistant August 2015 – May 2017

- Maintained, recorded, and organized resident and programing information
- Ensured the safety and academic success of 40 first year students in both social and academic issues
- Executed and utilized crisis management skills in various types of situations
- Created bulletin boards, door tags, and various forms of publicity
- Executed programs that were both interesting and conceptually captivating while operating on a budget of approximately $12,000
- Participated in monthly training updates to ensure policy knowledge and practices were up to date

Center for Analytics West Haven, CT

Data Entry Fall 2016 – Spring 2017

- Examined conflict, violence, terrorism activity, and military activity in the Middle East
- Worked on a government sponsored research project, exact details are protected under a strict non-disclosure agreement
- Affiliated with University of New Haven Criminal Justice Department

LEADERSHIP SKILLS

University of New Haven West Haven, CT

Alpha Phi Omega Fraternity – Xi Phi Chapter Fall 2015 – Spring 2018

- Assisted and mentored new members
- Completed 179.25 hours of community service for the chapter, surrounding community, college campus, and nation as a whole

Conclave Registration Chair Spring 2016 – Spring 2017

- Developed registration system for the Section 94/96 Conclave
- Aided in the planning of activities to be completed at the conference
- Performed registration and check in for all Alpha Phi Omega chapters in attendance on the day of the conference

Sergeant at Arms Spring 2016 – Fall 2016

- Updated and maintained Chapter Bylaws and Standard Operating Guidelines
- Maintained all Chapter property
- Served as parliamentarian and kept order within Chapter meetings

Undergraduate Student Government Association Representative Fall 2015 – Spring 2016

- Served as the direct connection between the chapter and the Undergraduate Student Government Association